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The impact of information laws on consumer credit access: evidence from Chile*

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Abstract

I study the impact on consumer markets from three laws that reduced the information of the Chilean credit bureau. A 2010 law deleted the delinquency information on short-term unemployed recipients. A 2011 law excluded borrower inquiries from the credit score. A 2012 law deleted the delinquency of borrowers with moderate amounts in arrears. Using a unique dataset, I show the 2010 law increased loan access, total credit and welfare, while the 2012 law had the opposite effect. The 2011 law had small welfare effects. This result is consistent with theoretical predictions that less borrower information can improve welfare if their effect on moral hazard is limited.

Resumen

Este artículo estudia el impacto en el mercado de créditos al consumo de tres leyes, implementadas entre 2010 y 2012, que han reducido la información pública disponible en el Directorio de Información Comercial (DICOM). La legislación de 2010 bloquea la publicación de la información de protestos y morosidades contraídas durante los períodos de cesantía que afecten a cada deudor. Una legislación en 2011 prohíbe predicciones de riesgo comercial que no estén basadas únicamente en información objetiva relativa a las morosidades o protestos de las persona, lo que impide la utilización del número de consultas realizadas a los antecedentes de crédito del deudor como un factor de riesgo comercial. La legislación de 2012 procedió a la exclusión del boletín comercial de los protestos y morosidades de mediano o bajo valor (definidas como obligaciones con un capital de impago total inferior a $2.500.000).
Utilizando una base de datos con un cruce de información entre el sistema bancario y la Encuesta Financiera de Hogares, yo encuentro que la legislación de 2010 aumentó el acceso al crédito, el crédito total y el bien-estar, al paso que la ley de 2012 tuvo el efecto opuesto. La legislación de 2011 tuvo un impacto muy bajo en el bien-estar total. Estos resultados son consistentes con predicciones teóricas de que menos información de crédito puede (en determinadas condiciones específicas) mejorar el bien-estar total, caso su efecto en el riesgo moral (“*moral hazard*”) sea limitado.

*Central Bank of Chile, Agustinas 1180, Santiago, Chile. Comments are welcome at carlosmadeira2009@u.northwestern.edu. I would like to thank seminar participants at the Central Bank of Chile, University Diego Portales, University of Santiago, IMF, Bundesbank, Federal Reserve Bank of Philadelphia and Federal Reserve Bank of New York. All errors are my own. Disclaimer: All the data used in this article (the EFH survey and the matched EFH-CMF dataset) are anonymized with pseudo IDs (not real IDs) and do not include personal identifiable information such as address or birth date, according to the laws of statistical secrecy in Chile.

1 Introduction

Around 88% of the countries have at least one credit bureau or registry (World Bank 2020). The credit information sharing role of these bureaus can improve debt access for borrowers (Jappelli and Pagano 2002, 2006), loan portfolio management for lenders (Liberman et al., 2018) and facilitate the monitoring of financial stability by regulators (Powell et al. 2004, World Bank 2020). Credit bureaus and registries allow several advantages through their role of information sharing on borrowers' credit history, including: i) higher accuracy of loan repayment probabilities, ii) reducing the information rents that lenders have on their customers' loan history, and iii) as a punishment device for borrowers who otherwise could default on unsecured debt or engage in Ponzi schemes by borrowing from multiple lenders (Jappelli and Pagano 2006). However, the optimal structure for a credit information sharing institution is still debatable, especially since these institutions can potentially harm risk sharing among debtors and increase privacy threats (Jappelli and Pagano 2006). The theoretical literature (Diamond 1989) and the empirical studies (Jappelli and Pagano 2002, World Bank 2020) are conclusive about the positive effects of some degree of information sharing about borrowers' loan history through credit bureaus or registries. However, it is less clear what aspects of the borrowers' history should be published and whether it can be optimal in some cases to publish less information (Padilla and Pagano 2000, Vercammen 1995, Elul and Gottardi 2015). For instance, it is not clear whether it is better to share information only for negative records (the history of defaults), a mix of banking and non-banking lender information (Foley et al. 2019), a mix of positive and negative records (Jappelli and Pagano 2006, Cowan and De Gregorio 2003) or whether records should be kept for a longer or a shorter period (Jappelli and Pagano 2006, Vercammen 1995, Elul and Gottardi 2015). Too little information can increase the market power of lenders (Padilla and Pagano 1997), while too much information sharing can decrease the effort of borrowers to keep up their reputation, reduce risk-sharing and prevent a fresh-start by able entrepreneurs (Vercammen 1995, Elul and Gottardi 2015). This question is increasingly relevant now as FinTechs are increasing the boundary of the information available on borrowers (Fuster et al. 2019, Frost et al. 2019, Berg et al. 2020).

This work contributes to this literature by studying the impact of three laws that reduced the information available from the credit bureau in Chile between 2010 and 2012. Most countries in the world have expanded the information available in their credit bureaus since the early 1990s (Jappelli and Pagano 2006, World Bank 2020), therefore the Chilean case provides an unique example to evaluate the effects of reducing the credit information of borrowers. Information deletion laws can have a positive impact on welfare, but only under special conditions since it is required that the law have a low impact on adverse selection and moral hazard while having a positive impact on incentives for entrepreneurial effort and risk sharing (Elul and Gottardi 2015). This article shows that the Chilean laws affected different kinds of credit information and also different types of borrowers, and therefore had distinct effects on debt access and loan repayment.

The first law (Law 20463, effective on October 25, 2010) is broadly termed as "Law on the credit information of the unemployed". The law introduced a delay for when the credit bureau can update the default information of workers currently receiving unemployment benefits. In particular, the credit bureau cannot report the delinquency or late payments of workers currently receiving unemployment benefits from the state, although such information can be legally included as part of the individuals' credit score after the unemployment compensation period is over (even if the worker has not yet regained employment at the end of his benefits). In Chile workers can only receive unemployment benefits for a short period (6 months or less), therefore the law gives incentives for unemployed workers to get a clean credit situation before the credit bureau makes their late payments and arrears public at the end of the unemployment insurance period. To implement the regulation, the credit bureau has access to the state's administrative records of all workers receiving unemployment benefits. The second law (Law 20521, effective July 23, 2011) is broadly termed "Law of credit reputation predictors' fairness". This law forbids the credit bureau from including non-default information as part of the borrowers' credit score number, although such information can still be included as part of the overall information provided by the credit report. The goal of the law was to facilitate the life of informal workers and small entrepreneurs who make a frequent use of checks or ask frequently for small loans, therefore such entrepreneurs were unduly hurt by lots of inquiries on their credit records to ascertain the validity of their checks and means of payment (Chilean Congress 2012). Finally, the third law (Law 20575, effective on February 17, 2012) is labelled as "Delinquency information deletion law". This law had three implications: i) excluding road charges from the credit score, ii) it forbids requests of the credit records for other purposes unrelated to credit decisions, such as employment recruitment, health and education selection processes, and iii) erasing the delinquency history for unpaid commitments of an amount below 2.5 million Chilean pesos (roughly 5,000 USD) registered at a date prior to December 31 of 2011. Notice that the law only affected the credit bureau's reports and did not constitute a debt forgiveness, since borrowers were still legally obliged to repay their creditors.

In a simple theoretical framework (based on Einav et al. 2010, Liberman et al. 2018) I show that the previous laws affected some groups which before the information deletion were separate, but now are harder to distinguish by lenders. Notice, however, that the laws represent more an obfuscation of different borrowers than a complete information deletion. In the case of the 2010 law, lenders can still request prospective borrowers for a copy of their employment contract and a statement of their wages in the previous months before making a loan decision. In the case of the 2011 law, lenders can still observe the last 6 months of inquiries on the borrower's credit report, but they no longer observe its impact on the credit score and therefore have a harder time to distinguish borrowers' repayment probabilities. The case of the 2012 law does imply a harsher obfuscation, since lenders can no longer request several of the records about borrowers' arrears before 2012.

To study the impact of the credit bureau information laws I use a unique dataset, which matches the real identities of households interviewed in the Chilean Household Finance Survey (*Encuesta Financiera de Hogares*, hence on EFH) and their banking credit history from administrative records kept by the Chilean Financial Markets Commission (in Spanish, Comisión para el Mercado Financiero, hence on CMF[1]). This provides a dataset of 9,720 households with their entire banking loan information for the period 2003 until 2018, and with cross-sectional information on the household demographic characteristics and income for one survey year (with survey years in 2007, 2008, 2009, 2010, 2011, 2014 and 2017). The matched data includes the loan history in the banking system for the interviewed persons plus survey reported measures of income, age and education for both the interviewed person and its household members (partner/spouse, parents or children).

The EFH-CMF data shows the households' access to new loans, the loan amounts and their subsequent delinquency at a monthly frequency from 2003 until 2018. I then build a set of variables that define the groups targeted by the new laws to estimate how these fared before and after the

[1]The CMF in Chile is the authority that represents both the Prudential Banking Authority and the Securities Exchange Commission, therefore it has full prudential powers to regulate and monitor all the banks, insurance companies, financial institutions, public stock listed companies and holding groups.

legislation. The first variable, a proxy for the groups targeted by the 2010 law, is the households' unemployment risk. This variable corresponds to an income weighted average of the unemployment probability of Chilean workers similar to the households' labor force members (Madeira 2018). This probability is both time-varying (with a quarterly frequency) and heterogeneous according to the industry, education, age, sex and region of the worker (Madeira 2019a). The second variables, a proxy of the groups targeted by the 2011 law, is a dummy for households that use checks as a payment or that made three or more loan applications in the past year. Finally, the third variable, a proxy of the group targeted by the 2012 law, denotes whether households had a total amount of debt in arrears below 2.5 million pesos by the end of 2011.

The results show that the 2010 law had a positive impact on loan access, debt amounts and welfare, while reducing interest rates for a significant fraction of the borrowers. Both the 2011 and 2012 laws reduced interest rates for a fraction of the borrowers, but increased interest rates for other borrowers. Furthermore, the 2011 and 2012 laws both implied a reduction in loan access and debt amounts, with the 2012 law having a much larger impact. The 2012 laws implied a reduction in welfare, while the 2011 law had almost no welfare impact. Overall, the three laws combined was negative for welfare, although some borrowers benefitted from higher credit access.

This work is related to a growing body of research studying the effects of credit information on borrowers' outcomes (Jappelli and Pagano 2006, Han and Li 2011, Elul and Gottardi 2015). In particular, Liberman et al. (2018) studied the 2012 Chilean law (the delinquency deletion law), showing it had a small negative impact on many borrowers, while having a moderate positive impact on a few. We improve upon their study by showing that the Chilean credit information laws implemented in 2010 and 2011 showed several positive aspects for the credit market and therefore not all the Chilean legislation was negative unlike the analysis of the 2012 law. Herkenhoff et al. (2016) and Bos et al. (2018) find that deleting negative credit reports in the US and Sweden had a positive impact on employment, while Liberman (2016) shows that some Chilean borrowers benefitted from renegotiating delinquent loans in order to gain better credit subsequently. In theoretical terms, the study by Elul and Gottardi (2015) shows that credit information deletion can be positive for welfare if its impact on adverse selection is small, while the effect on borrowers' future effort and entrepreneurial projects is positive. This article provides empirical evidence of legislation that may fill such criteria. The 2010 law is an example of a legislation with such characteristics, since it targets the unemployed, which is a group of borrowers that may have suffered a negative shock that is unrelated to strategic default reasons, and it gives them just a short period of respite before their delinquency becomes public, therefore increasing the incentives to repay the loans before the deadline. The Chilean 2010 law's protection of the unemployed may also constitute an improvement in terms of risk-sharing and a reduction in reclassification risk (as was found in the analysis of health insurance pricing in the US, see Handel et al. 2015). In the same way the 2011 Chilean law had the intention of benefiting small entrepreneurs that often use checks and small loans, but may have been unduly hurt by the credit scoring formula.

This work is organized as follows. Section 2 summarizes the Chilean credit information laws and the EFH-CMF data. Section 3 explains the empirical strategy for measuring the laws' impact. Section 4 details the estimation results, while section 5 summarizes the policy implications.

2 Data description and institutional setting

2.1 The Chilean credit bureau

The Chilean credit information system operates through two main institutions: i) a public credit register managed by the Chilean Financial Markets Commission (CMF), ii) a privately managed credit bureau operated by Equifax Inc. The public credit register collects for the purpose of bank supervision the entire history of banking loans of each borrower (firms or persons) in Chile. The public credit register can only be accessed by banks and some regulated financial institutions, which can obtain info on the borrower's current banking loans and delinquency status but not the entire banking loan history (the lender obviously knows the credit history of its own borrowers with itself, but not with other institutions). Access is given only to check the borrower's loan applications and it is illegal for lenders to keep the borrowers' CMF credit records.

The private credit bureau managed by Equifax represents the most universally used source of credit reputation in Chile, both by banks and by non-bank lenders such as retail stores. In Chile there is a compulsory national identifier for each person and firm, which makes it straightforward for the bureau to uniquely identify a borrower and to match information from multiple private and public datasets. Therefore the credit bureau publishes a report with a substantial amount of information on the borrower, with a mix of personal identification data, negative credit history information, plus some positive information on assets and income. The personal identification data of the credit report includes the national ID of the borrower, plus his name, employer's ID, last 6 residential addresses, emails, phone contacts, gender, nationality, birth date, civil status and marriage date from the official civil register. The negative credit information is mostly collected from delinquency notices by lenders, landlords and the tax administration. The delinquency notices are complemented with other sources of risk information, such as data from commercial databases on privately owned businesses (plus the delinquency history of such businesses and the and spouses. Furthermore, there is positive information on the ownership and estimated value of businesses, real estate and vehicles from property registers. The credit bureau also includes its estimate of the borrower's socioeconomic status and whether its value belongs to a range within the percentiles 90-100, 70-89, 40-69, 39-8, 1-7, with higher percentiles implying higher income.

The private bureau report's most salient info is the borrower's total amount of debt in arrears and its Risk Indicator (i.e., the credit score). Banks, commercial exchanges, the labor and social security administration, customs agencies, courts, notaries and real estate curators are obliged by law to inform the bureau of any debt arrears of their borrowers every 15 days. The borrower's debt in arrears is shown separately for arrears late between 30 and 60 days, 61 and 90 days, and more than 90 days. Besides loan arrears, the report includes unpaid rents, taxes, social security contributions plus unpaid debts of the spouse and businesses. The credit score is a number between 1 and 999 provided by a confidential model, with higher values associated with lower risk. The credit report also includes the Risk Indicators of the previous 12 months and an EverClean Dummy Indicator of whether the borrower always had a perfect credit score for the last 36 months. The report also lists the number and identities of the companies and individuals that requested the borrower's credit report over the last 6 months. Finally, since 2002 (Law 19812, "Protection of privacy") the bureau's Risk Indicator cannot include delinquencies for utilities (gas, electricity, water), loan arrears that were already repaid or renegotiated, nor debts older than 5 years[2]. However, lenders may still partially detect past delinquencies that were repaid, since that information still counts for

[2] Chile does not allow for personal bankruptcy, only for businesses. Even if loan arrears are "forgotten" by the credit bureau, such debts are still valid by law and can be demanded in courts. However, debts may become hard to execute in the court system if lenders wait too long before requesting a legal proceeding or loan collection.

the reported Risk Indicators of the last 12 months and the EverClean value.

This institutional setting has remained largely stable since 1999, although some laws affected what information can be included in the credit report, which factors can be accounted for in the Risk Indicator model and for what purposes can the information be used. Perhaps the most relevant changes to the private credit bureau's functioning were the three laws already briefly described in the introduction, which were legislated between 2010 and 2012.

The first law (Law 20463, "Law on the credit information of the unemployed", effective on October 25, 2010) blocks the credit bureau from reporting the loan arrears of workers currently on unemployment benefits. Therefore now unemployed beneficiaries have a short period of 6 months or less to repay their delinquencies[3]. To implement the regulation, the credit bureau has access to the state's administrative records of unemployment beneficiaries.

The second law (Law 20521, "Law of credit reputation predictors' fairness", effective July 23, 2011) forbids the credit bureau from including non-default information as part of the borrowers' credit score number (i.e., the Risk Indicator). Note, however, that the law still allows non-default information to be included as part of the overall information provided by the credit report. The goal of the law was to facilitate the life of informal workers and small entrepreneurs who make a frequent use of checks or ask frequently for small loans (Chilean Congress 2012). Before this law, there were 3 main factors behind the bureau's credit score model: i) debt proceedings or collections, ii) the number of payments in arrears (loans or installments), iii) the number of inquiries on the borrower's score. On the 31st of January of 2011 a Chilean court ruled the number of inquiries on the borrower as an unconstitutional factor for credit scoring models, since the legal reasoning argued that inquiries could be initiated by any interested person or business and therefore this variable was outside of the control of the borrowers[4]. For instance, a business or person could request a

[3]Since January 2009, workers with permanent and fixed term contracts only receive state unemployment benefits for a maximum of 5 and 3 months, respectively. The unemployment insurance only covers formal contracts, therefore workers in the informal economy (around 20% of the Chilean labor force) are not covered and cannot be targeted by the credit information law of 2010. The 2010 law allows workers that receive unemployment benefits for less than 6 months to formally request the credit bureau to avoid the publication of their delinquencies for a total of 6 months.

[4]In other countries, such as the US, credit bureaus may differentiate between "soft" (processes unrelated to loan applications) and "hard" inquiries, which correspond to inquires made specifically for a loan application requested by the borrower. For the FICO score in the US only "hard" inquiries are taken into account. The reason is that "hard" inquiries from too many loan applications may be related to moral hazard and an attempt of the borrower to contract

credit report of any person not to evaluate a loan request, but simply to check whether he would be a good client, a person of reputation or an owner of assets. The judicial court's ruling sparked a Congressional debate, which initiated the law that only explicit delinquency information could be taken into account as an element of the bureau's credit scoring model. In particular, the Congress wished to protect small and informal entrepreneurs who have many inquiries on their reports due to their frequent use of checks or small loan requests. However, it is relevant to note that the credit bureau is still allowed to include the firms and persons non-delinquency information as part of its credit reports. The number of inquiries (plus the date and identity of the person or business making the inquiry) in the last 6 months is still included in the credit report. Also, as noted above the bureau's credit report is allowed to include information on the borrowers' personal civil status, its estimated socioeconomic strata, plus their assets (real estate, vehicles), among other loan-related information. The only thing that the 2011 law forbids is that the bureau takes such information and then use it as a part of the credit score number (i.e., the Risk Indicator) of the person or firm, since the legislation interprets that could be damaging to the reputation of good and respectable borrowers that are poorer according to some dimensions[5]. Prospective lenders, however, can still take the non-delinquency information as part of their business decision as additional elements to the credit score number. The 2011 law therefore does not entirely block lenders from distinguishing firms or persons with several loan inquiries or negative non-loan related information, but it makes it harder to do so since lenders may be less sophisticated in their use of databases and may have more difficulty in associating such information in terms of a quantitative default risk number.

The third law (Law 20575, "Delinquency information deletion law", effective on February 17, 2012) had three implications: i) excluding road charges from the credit report, ii) it forbids report requests for purposes unrelated to credit decisions, such as employment, health and education

too much debt before default or bankruptcy (Jappelli and Pagano 2006). The Chilean credit bureau, however, does not separate between hard and soft inquiries. It gives a list of inquiries over the last 6 months, whether made by banks, cell-phone companies or other stores, plus the date of such inquiries. Even the inquiries made by banks do not indicate whether the motive was "hard" because of a loan request or "soft" for other reasons.

[5] For instance, a borrower could have a perfect credit score because it has never shown any delinquency, but the report adds other information about whether it has a low socioeconomic status (due to low education, for instance) and low assets. After the 2011 law, lenders may still look at such information and decide that such a borrower is not a good business opportunity and refuse him credit. The only thing that the 2011 law forbids is that the credit bureau states explicitly that such a borrower has a high credit risk due to low socioeconomic status and few assets.

processes, iii) erasing delinquency reports of a total amount below 2.5 million Chilean pesos (roughly 5,000 USD) by December 31, 2011. The law was partially motivated by the 2010 earthquake and did not constitute a debt forgiveness, since borrowers were still legally obliged to repay (Chilean Congress 2012). However, financial industry agents expressed some concern about the law's consequences on future commitments, since a previous law one decade before made a similar disposition of deleting delinquencies below 2 million pesos from the credit bureau (Law 19812, effective on June 13, 2002). Therefore a similar legislation could create the dangerous expectation that such delinquency deletion may happen every ten years. Furthermore, the impact of the 2012 law was large, since it erased the delinquency information of 67% of the borrowers in Chile or about 21% of the adult population (Liberman et al. 2018). The 2012's information deletion ceased to have any effect after January 2017, since the bureau erases debt arrears after 5 years anyway.

2.2 The EFH-CMF data

The Chilean Household Finance Survey (EFH) is a cross-sectional survey that covered a total of 21,319 urban households over the period 2007 until 2017 (waves 2007, 2008, 2009, 2010, 2011, 2014 and 2017). To obtain a more accurate view of the evolution of each household's indebtedness over time, the Central Bank of Chile and the Chilean Financial Markets Commission (CMF) decided to build an EFH-CMF dataset, where each survey's information is linked to the monthly banking credit information for each month over the period between January 2003 and December 2018. The link between each household's main member on the survey dataset and its history of banking debt is made by using the Chilean national identity numbers. Chileans make regular use of their national ID to obtain discounts in the supermarket chains, apply for loans, or to use the health system, therefore participating households are comfortable in providing their information during the survey interview. Furthermore, each national identity number is followed by a validation digit, which allows to test whether the stated number is correct. The EFH survey respondents are then matched with the CMF administrative records, which include all the people who have ever applied for a banking product (whether a loan, a current account or a savings account)[6]. A matched EFH-CMF dataset

[6] The EFH-CMF dataset has some limitations: i) the universe is limited to individuals who ever applied for or used a banking product; ii) the monthly loan history is limited to banking loans of different types (consumer installment

was obtained for 9,720 households (note that a significant fraction of the Chilean population is unbanked and therefore outside of the CMF records). The data in this article (the EFH survey and the matched EFH-CMF dataset) are anonymized with pseudo IDs and do not include personal identifiable information such as address or birth date, according to the laws of statistical secrecy.

The matched EFH-CMF dataset provides the households' banking loan history (mortgages, consumer installment loans, credit cards and credit lines) with a monthly frequency and their self-reported cross-sectional survey information on the household demographic characteristics (such as age, education, partners and children), income and loans (with banks and non-banking institutions).

The EFH survey has limited data on income volatility and unemployment, because it is a cross-sectional survey and therefore it only measures self-reported unemployment at the month of the survey. It is therefore not possible to observe the entire unemployment history of the household members and to check which ones were unemployed before and after the 2010 law regulating the credit history of the unemployed. For this reason I use the unemployment risks of the EFH workers based on the mean statistics for workers with similar characteristics from the Chilean Employment Survey (ENE), conditional on their education, age, industry, income quintile and region (Madeira 2018, 2019a). Each household i's permanent income is obtained as the sum of its non-labor income (a_i) plus the labor earnings of each labor force member k: $P_{i,t} = a_i + \sum_k P_{k(i),t}$. The permanent income of each household member is given by $P_{k(i),t} = (Y_{k,i}(1 - u_{k,i,t}) + Y_{k,i} RR_{k,i} u_{k,i,t})$, where $Y_{k,i}$ is worker k's earnings when in employment, $u_{k,i,t} = u(x_{k(i)}, t)$ is its probability of being in an unemployment spell, and $RR_{k,i}$ is its replacement ratio of income during unemployment relative to the earnings while working (Madeira 2018). Also, the unemployment risk of the household is estimated as a weighted average of the unemployment risk of its labor force members, using each member's permanent income as a weight: $\bar{u}_{i,t} = \sum_k \frac{P_{k(i),t}}{P_{i,t} - a_i} u_{k(i),t}$.

Note that both the household's permanent income and unemployment risk differ over time, because the unemployment probabilities of each worker type, $u_{k,i,t} = u(x_{k(i)}, t)$, change at a quarterly frequency. Also, the household's permanent income is the sum of each member's expected income when working or not, therefore it differs from the current income.

loans, credit cards, lines of credit, student loans and mortgages) and does not include other lenders such as retail stores, unions or car dealers; iii) the data provides information on the current loan amount, the original loan amount at the time the contract was made, the total payment due to that loan in a certain month and whether the loan is in delinquency, but it does not include information on renegotiation of loans, interest rates, plus other fees charged.

Figure 1: Aggregate time-series (log-deviations from the mean) for the number of debtors, total debt amount and ratio of consumer debt to permanent income for the EFH-CMF sample

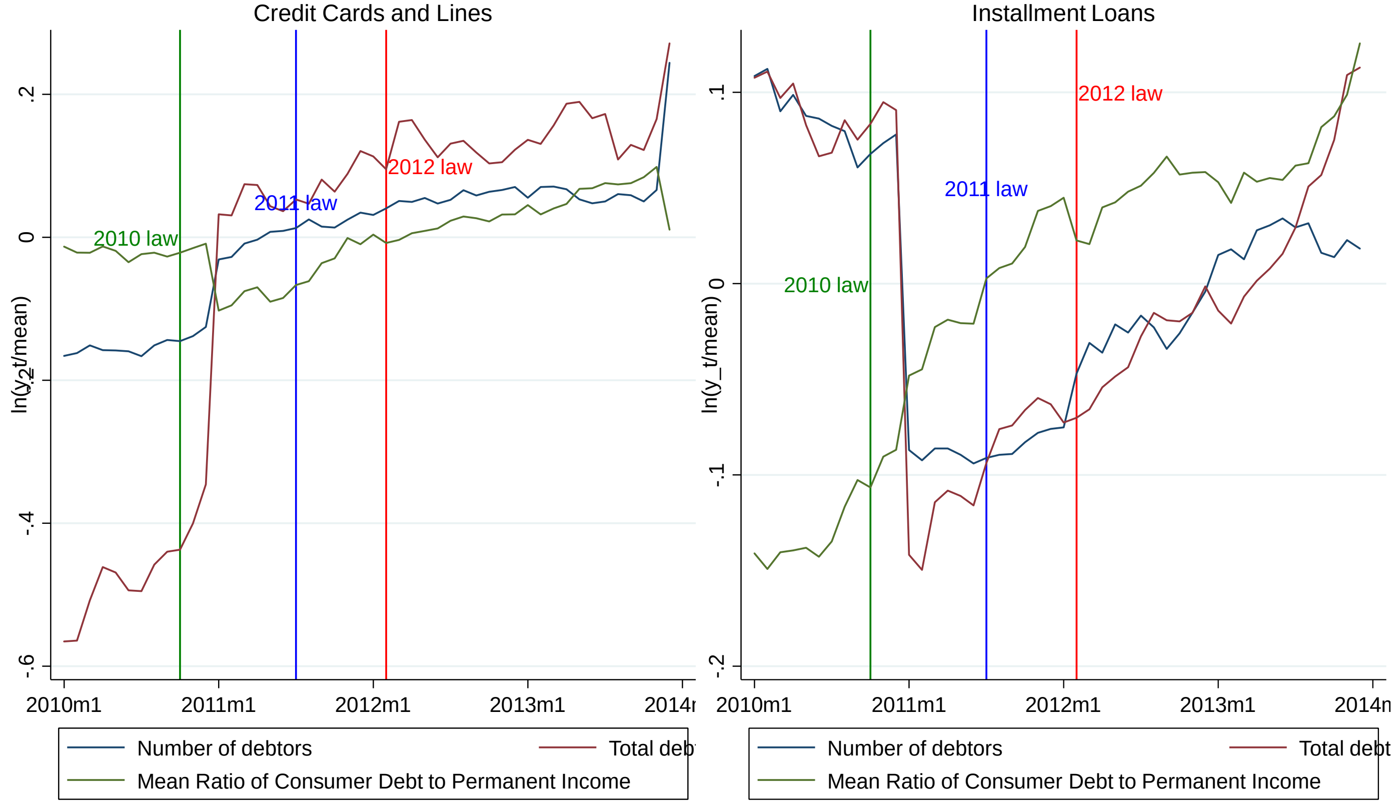

Figure 1 summarizes the EFH-CMF sample's aggregate values for the number of debtors, total debt (sum of the consumer debt across all borrowers) and the ratio of consumer debt to permanent income (mean across all borrowers). All series are at a monthly frequency and expressed as log-deviations from the mean for easiness of exposition. The figure concentrates on the period of 2010 until the end of 2013, in order to visualize best their evolution around the timing of the 2010, 2011 and 2012 laws. Notice, however, that these laws were not the only aggregate shocks to affect the credit market during this period. In fact, the 2010 law was preceded by a large earthquake in February of 2010 and by a recession, caused by the Global Financial Crisis, that affected almost the entire year of 2009. As a reaction to the 2009 recession and the 2010 earthquake, there was a strong decrease in the number of borrowers and total debt for consumer installment loans, although there was a significant increase in the number of borrowers using credit cards and lines of credit for short-term liquidity needs. In the beginning of 2011, Chile experienced a strong economic recovery, which implicated a trend growth for the number of consumer borrowers, total debt and the ratio of debt to permanent income for both consumer installment loans and credit cards plus lines of credit. Due to the presence of these aggregate shocks it is not possible to test the impact of each legislation using time series data, therefore the analysis requires using the microdata to separate between the law's affected borrowers and a similar control group.

2.3 The Chilean consumer credit market

Households in Chile have consumer loans with many kinds of lenders, therefore this section summarizes how banking and non-banking institutions compete for borrowers. I classify all the EFH households into 7 mutually exclusive categories of borrowers according to their largest consumer loan amount held: 1) households with consumer loans in Banks (but not in Retail Stores), 2) households with consumer loans both in Banks and Retail Stores, 3) households with consumer loans in Retail Stores (but not in Banks), 4) households with consumer loans in Labor and Credit Unions[7], 5)

[7] Labor Unions in Chile can extend loans to their members, but have some restrictions relative to other lenders. In particular, unions cannot charge different interest rates according to the borrower profile (that is, union loans can have different interest rates according to its maturity and loan amount, but the same offer must be given to all borrowers). However, unions have the advantage that the credit can be paid directly from a fraction of the wage transfers of the employer, therefore unions will receive some payment even if the borrower chooses to engage in strategic default.

households with Other Loans (loans at car lenders, pawnshops, informal loans), 6) households with No Desire for Debt, and 7) households with No Access to Debt (either because their loan applications were rejected or because they expected the applications to be rejected). Since these borrower categories are mutually exclusive, their sum captures 100% of the sample. The EFH survey also has information on the motives why borrowers took their loans[8].

Furthermore, I classify the EFH households according to whether these can be seen as beneficiaries of the 2010, 2011 and 2012 laws. For the 2010 law, I create a dummy variable for whether the household is a possible beneficiary of the legislation, according to whether it reports at least one member as being unemployed at the time of the survey[9]. For the 2011 law, households are classified as targeted beneficiaries of the legislation if they reported that they use checks frequently or if they requested three or more consumer loan applications in the previous year[10]. For the 2012 law, households are classified as possible beneficiaries if these reported bank loans in arrears below 2.5 million pesos at the end of 2011 or if they reported a total amount of loan arrears (including bank and non-banking debts) for a survey interview date before 2012[11].

Using all the cross-sectional EFH waves (2007-2017) as a pooled dataset, Table 1 summarizes the demographic profiles for the Chilean households, the target beneficiaries of the laws, plus the households with some type of consumer debt. According to our definition criteria, around 12.5%,

[8] The loan purposes are classified under 13 motives: 1) "Purchase of articles for the home and living expenses", 2) "To purchase clothes", 3) "Purchase, maintenance and repair expenses of vehicles", 4) "Vacations", 5) "To finance a business or professional activity", 6) "For investment in financial assets", 7) "To refurbish or renovate the residence", 8) "For education purposes", 9) "To purchase real estate assets", 10) "To provide funds or make a loan to another person or relative", 11) "To pay previous debts or consolidate other consumption debts", 12) "Medical treatment", 13) "Other". To summarize the loan motives in a better way, I aggregate the results into 4 larger categories, with category 1 being "Current consumption" (the sum of purposes 1, 2, 13), category 2 being "Durable goods and investments" (the sum of purposes 3 to 10), category 3 being "Pay other debts" (purpose 11) and category 4 being "Health" (purpose 12). Vacations represent an infrequent expenditure and a large item in households' budgets, therefore these are financed and classified as semi-durable expenditure goods for measurement purposes (Madeira, 2019b).

[9] The EFH survey does not measure the duration of the unemployment spell.

[10] According to the EFH pooled sample, 68.4% of the borrowers report only one loan application in the last 12 months, while 89.2% of the borrowing households did two or fewer loan applications. Households with 3 or 4 loan applications in the last 12 months represent 8.7% of the borrowers, while households with 5 loan applications or more represent less than 2.1% of the borrowers. For this reason and given the limited size of the sample, I include all households with 3 or more loan applications as possible beneficiaries of the law.

[11] This accounts that delinquent borrowers with non-banking loans can also benefit from the 2012 law.

14.2% and 8.5% of the households benefitted from the 2010, 2011 and 2012 laws, respectively. Most of the beneficiaries of the 2011 law (87% of them) fill such criteria for their frequent use of checks and not because of their number of loan applications. Some interesting differences across the beneficiaries of each law are easy to assess. Around 73% and 94% of the 2011 and 2012 law's beneficiaries, respectively, have some sort of consumer loan, which is a much higher rate than the other households. This makes sense since these laws were targeted specifically at households with many loan applications (in case of the 2011 law) and delinquencies (in case of the 2012 law). It is also interesting to note that the beneficiaries of the 2011 law have much higher education, income and lower unemployment risk than the other households. This makes sense since the law targeted entrepreneurs and self-employed that made a high use of checks and loan applications. Therefore high income entrepreneurs could have benefitted as much as the lower income and informal entrepreneurs that concerned the policy makers. More than half of the beneficiaries of the 2011 legislation (the "Risk predictors' fairness" law) have a college education or higher, while less than 20% of the beneficiaries of the 2010 (the "Credit information of the unemployed" law) and the 2011 legislations (the "Delinquency deletion" law) have completed college. Also, the distribution of permanent income - according to the percentiles 25, 50 and 75 - shows that the beneficiaries of the 2011 law are substantially wealthier than the beneficiaries of the 2010 and 2012 laws. Notice, however, that the beneficiaries of the 2010 law have a substantially higher unemployment risk ($u_{i.t}$), while the 2012 beneficiaries are substantially poorer (according to the percentiles of the log permanent income, $\ln(P_{i.t})$). Analyzing borrowers of each lender type, it is easy to access that households with loans in Banks and Other debts have more education, income and less unemployment risk than other borrowers. It is also interesting to observe that the 2011 law had more beneficiaries with loans in Banks (or Banks and Retail), while the 2012 law had more beneficiaries among Retail (or Banks and Retail) borrowers.

Table 2 summarizes the share of each borrower type as a percentage of the total household population, the total consumer debt amount per household, and the share that each loan motive represents as a percentage of the total consumer debt of the borrowers. The major lenders in Chile are Banks and Retail Stores, with 9.4%, 26.4% and 13.9% of the households having loans with only Banks, only Retail Stores, and both Banks and Retail Stores, respectively. Also, 26.9% of the households have no consumer debt because they wish so, while 11.6% do not have access to

Table 1: Income and demographics of the target beneficiaries of the laws

	College educ.	$u_{i.t}$	Age (years)	$\ln(P_{i.t})$ P25	P50	P75	Debtor	Uses checks	Beneficiary of law 2010	2011	2012
All Households	23.9	4.1	47.8	13.1	13.7	14.3	61.5	12.3	12.5	14.2	20.3
Beneficiary 2010 law	19.5	6.0	48.6	13.2	13.7	14.3	65.4	9.0	100	11.1	23.0
Beneficiary 2011 law	53.3	2.8	48.5	13.9	14.5	15.0	72.9	87.2	9.8	100	21.5
Beneficiary 2012 law	21.0	4.1	47.1	13.1	13.6	14.2	81.7	10.4	14.2	15.0	100
All Borrowers	24.4	4.2	47.1	13.2	13.7	14.3	100	14.3	13.3	16.8	26.9
Banks	38.9	3.6	46.7	13.4	14.1	14.7	100	30.9	10.5	32.1	27.5
Banks and Retail Stores	30.0	3.9	46.4	13.3	14.0	14.6	100	25.2	13.3	30.3	33.7
Retail Stores	11.8	4.7	48.2	13.0	13.4	13.9	100	4.3	13.7	5.6	24.0
Unions	16.2	3.9	50.5	13.3	13.7	14.2	100	3.6	13.6	6.7	25.0
Other Debts	41.1	4.1	42.2	13.6	14.1	14.6	100	17.5	15.8	20.5	25.0
No Desire for Debt	26.4	3.5	49.6	13.1	13.7	14.3	0	12.2	9.7	12.6	9.3
No Access to Debt	13.7	4.5	49.0	12.8	13.3	13.8	0	2.4	14.8	3.8	10.5

EFH (2007-2017). All the values are in percentage points, except for the log permanent income: $\ln(P_{i.t})$.

consumer loans although they wish so. Retail Stores and Unions specialize in smaller loans. It is interesting to note some differences across the beneficiaries of the laws. The beneficiaries of the 2011 law have much larger loans and also present a higher share of debt motivated by the purchase of "Durable" goods (which includes loans targeted for assets and vehicles), as expected for a segment of small entrepreneurs. Also, the beneficiaries of the 2012 law present a very high share of debt motivated by the purposes of "Consumption" and "Pay previous debts". The beneficiaries of the 2010 law have smaller loans relative to the other borrowers, which makes sense in a segment that was targeted due to a negative income shock (unemployment) instead of a debt behavior.

The EFH survey includes measures of the households' delinquency behavior for each loan since 2010. Before 2010 the EFH survey recorded only a rough measure of whether the household was delinquent on any consumer loan in the previous year, but it did not measure delinquency on a loan-by-loan basis. For the case of credit cards there is not a standard measure of delinquency, since lenders can choose to turn the unpaid fraction of the credit as a revolving debt for the next month. However, the survey records whether households were unable to pay the minimum amount required by their credit cards, which is a rough measure of payment difficulties. Table 3 summarizes the delinquency and credit card payment difficulties across different lenders. The riskiest borrowers are those with major loans in Retail Stores or with both Banks and Retail Stores, while borrowers with Unions and Other Debts have lower delinquency rates. Table 3 also shows that the 2012 law's

Table 2: Debt share of motives by borrower type for all households and beneficiary targets of the laws

Borrower type	Population[a]	Consumer debt (mean)[b]	Consumption	Durables	Pay debts	Health
		All Households				
Banks	9.4	150.6	46.9	31.3	16.6	5.2
Banks and Retail Stores	13.9	183.8	52.6	23.3	18.4	5.7
Retail Stores	26.4	25.5	87.4	4.9	4.3	3.3
Unions	5.7	60.3	40.1	25.2	20.4	13.2
Other Debts	6.0	233.9	42.7	50.9	4.6	1.8
No Desire for Debt	26.9					
No Access to Debt	11.6					
Total Borrowers		103.1	64.6	19.5	10.9	4.9
		Beneficiaries of the 2010 law				
Banks	7.9	98.0	42.5	29.1	20.6	7.6
Banks and Retail Stores	14.8	149.6	54.3	19.4	20.8	5.5
Retail Stores	28.9	26.1	88.3	3.3	5.5	2.9
Unions	6.2	43.4	38.1	25.2	22.3	10.9
Other Debts	7.6	218.4	49.6	42.1	6.0	2.3
No Desire for Debt	20.9					
No Access to Debt	13.7					
Total Beneficiaries		85.5	65.8	16.6	12.4	4.7
		Beneficiaries of the 2011 law				
Banks	21.3	238.7	41.0	36.6	17.6	4.8
Banks and Retail Stores	29.8	291.4	48.2	28.3	17.4	6.0
Retail Stores	10.4	45.0	78.1	11.4	7.0	3.4
Unions	2.7	130.5	29.0	23.0	34.0	14.1
Other Debts	8.7	339.2	34.6	59.3	4.4	1.6
No Desire for Debt	23.9					
No Access to Debt	3.1					
Total Beneficiaries		239.9	48.1	31.8	15.0	5.0
		Beneficiaries of the 2012 law				
Banks	12.7	167.8	44.3	28.9	20.2	6.3
Banks and Retail Stores	23.2	176.1	54.1	18.0	20.2	7.7
Retail Stores	31.3	32.4	86.9	3.6	5.8	3.7
Unions	7.1	82.4	40.6	23.9	26.2	9.4
Other Debts	7.4	211.0	51.0	38.1	8.9	2.0
No Desire for Debt	12.4					
No Access to Debt	6.0					
Total Beneficiaries		113.9	63.7	16.5	14.2	5.6

EFH waves (2007-2017). All the values are in percentage points, except *b*) which is in UF.
a) Population is given as a percentage of all the households in Chile.

Table 3: Delinquency rates by borrower type (EFH, waves 2010-2017)

Borrower type	Consumer debt delinquency (any loan)		Banks' consumer loan delinquency[a]		Credit card payment below minimum[a]	
	≥1 month	≥3 months	≥1 month	≥3 months	Banks	Retail Stores
All Households						
Banks	15.9	7.6	16.1	7.5	3.6	
Banks and Retail Stores	17.5	10.6	16.1	9.9	7.1	12.6
Retail Stores	19.4	11.5				18.2
Unions	9.0	5.7	16.1	10.5	3.4	12.5
Other Debts	5.3	3.0	13.6	6.3	1.6	7.2
All Borrowers	13.5	7.8	16.0	8.8	3.8	13.8
Beneficiaries of the 2010 law						
Banks	21.5	5.9	19.3	6.1	5.7	
Banks and Retail Stores	18.7	10.5	18.7	10.4	11.4	19.3
Retail Stores	18.6	12.0				22.7
Unions	13.8	8.9	32.2	0.0	0.9	9.6
Other Debts	8.8	4.5	29.7	13.2	1.1	10.5
All Beneficiaries	15.9	8.4	19.9	8.7	5.0	17.7
Beneficiaries of the 2011 law						
Banks	6.1	2.7	5.7	2.8	1.2	
Banks and Retail Stores	9.7	4.8	6.3	3.4	3.0	5.4
Retail Stores	20.5	8.7				7.3
Unions	20.8	8.4	18.8	0.0	12.2	5.8
Other Debts	4.1	2.7	7.7	3.3	2.2	4.7
All Beneficiaries	8.6	4.1	6.3	3.1	2.4	4.9
Beneficiaries of the 2012 law						
Banks	34.1	18.6	34.2	18.1	10.5	
Banks and Retail Stores	35.6	23.2	34.3	22.2	18.1	29.2
Retail Stores	39.3	25.8				49.2
Unions	17.9	12.0	28.8	13.7	1.8	28.7
Other Debts	15.9	8.6	36.0	13.9	1.5	18.1
All Beneficiaries	29.3	18.2	34.2	20.0	10.1	34.2

All values are in percentage points.

[a] Note that the mutually exclusive categories of the borrowers are based on their largest debt amount. Therefore borrowers with their largest loans in Unions and Retail Stores may also have small loans and credit cards with Banks or Retail Stores.

beneficiaries had very high rate of delinquency rates. Of the 2012 beneficiaries, 44.5% and 27.2% were in arrears at 30 days and 90 days or more, respectively. The 2010 law's beneficiaries were only slightly more delinquent than the average across all borrowers. Finally, the 2011 law's beneficiaries were significantly less delinquent than the average borrower. The delinquency rates at 30 and 90 days or more were just 8.6% and 4.1% for the 2011 beneficiaries, which are much lower values than the 13.5% and 7.8% rates observed for the average borrower. It appears therefore that adverse selection was not big for the 2010 and 2011 beneficiaries, an hypothesis that will be tested next.

3 Theoretical framework and empirical strategy

3.1 Theoretical framework

The economic theory is unclear about the effects of information deletion on total credit, default and welfare. A positive impact on credit and welfare can happen if "adverse selection" and "moral hazard" are not too big (Elul and Gottardi 2015). Here I follow a general framework, similar to Einav et al. (2010) and Liberman et al. (2018), for measuring the impact of information on adverse selection and welfare. Let borrowers belong to K types, $k = 1, 2, .., K$, with each type k presenting a default-rate Df_k, loan demand $q_k(R_k)$ and profit-neutral interest rate R_k.

To frame the 2010 law, think of 4 groups, with $k = 1, 2, 3, 4$, being labelled respectively as borrowers with no default history, borrowers with some recent default and a short-term unemployment spell, borrowers on a long-term unemployment spell (i.e., longer than 6 months) and with a default history, borrowers with a default history unrelated to unemployment (for example, strategic default, inattention, health, health or family problems). Before the 2010 law lenders observe only 2 groups which can be expressed as $k = 1, 2 + 3 + 4$. After the 2010 law, lenders again observe only 2 groups which can be expressed as $k = 1 + 2, 3 + 4$. Note that the 2010 law does not necessarily imply a loss of information for lenders, only a regrouping of unobservable groups into 2 different groups. The 2011 and 2012 laws can be framed in a similar way. Before the 2011 law, lenders could observe the groups $k = 1, 2, 3$, which represent respectively the borrowers with a clean credit history, borrowers with hard and soft inquiries, borrowers with delinquencies. After the 2011 law, lenders still observe $k = 1, 2, 3$, but they only know the credit scores of the groups $k = 1 + 2, 3$ and therefore it is harder for some lenders to separate the loan offers for groups 1 and 2. Before the 2012 law, lenders observe $k = 1, 2, 3$, which represent respectively the borrowers with a clean credit history, borrowers with median and low arrears, borrowers with large arrears. After the 2012 law, lenders only observe $k = 1 + 2, 3$, since the group with median and low arrears is pooled with the clean borrowers.

For each group there is an additional relevant information which can be observed when $z = 0$ for a fraction α of the borrowers and is unobserved or obfuscated when $z = 1$ for a fraction $1-\alpha$ of the borrowers. Let the credit demand function and the statistical delinquency probability of each type be: $q_{z,k}(R)$ and $Df_{z,k}(R, q_{z,k})$. Lenders are competitive and offer a rate at their average cost of credit, expressed as a risk-adjusted interest rate (RIR): $RIR_z(R, q_{z,k})$. Before the information deletion we have an equilibrium interest rate R^e_z and credit quantity $q^e_{z,k}$ for each value of z, which is subject to clearing the demand condition $q^e_{z,k} = q_{z,k}(R^e_z)$ and to the competitive zero profit condition $R^e_z = RIR_z(R^e_z, q^e_{z,k})$. After the legislation that makes it difficult for lenders to observe z, then the new competitive equilibrium forces lenders to charge a single interest rate R^e and borrowers now each demand credit at the same pooled rate $q^p_{z,k} = q_{z,k}(R^e)$. Therefore the new competitive zero profit condition becomes $R^e = RIR^e(R^e, q^p_{z=0,k}, q^p_{z=1,k}) = \alpha RIR_{z=0}(R^e, q^p_{z=0,k}) + (1-\alpha)RIR_{z=1}(R^e, q^p_{z=1,k})$, with the new interest rate being a weighted function of each unobserved type of borrower. The deadweight loss for each group z is given by the difference in consumer surplus, CS: $DWL_{z,k} = CS(q^e_{z,k}, RIR_z(R^e_z, q^e_{z,k})) - CS(q^p_{z,k}, RIR^e(R^e, q^p_{z=0,k}, q^p_{z=1,k}))$. Summing the deadweight loss across all groups, then we get $DWL = \sum_{k=1}^{K} \alpha DWL_{z=0,k} + (1-\alpha)DWL_{z=1,k}$. A positive legislation change would show a negative deadweight loss ($DWL < 0$).

3.2 Empirical model

For estimating the credit demand and delinquency probability functions ($q_{z,k}(R)$, $Df_{z,k}(R, q_{z,k})$), I consider a reduced-form econometric approach, in the same manner as previous empirical studies of consumer loan default (Gross and Souleles 2002, Gerardi et al. 2018, Liberman et al. 2018, Berg et al. 2020, Madeira 2019b). The empirical analysis considers 4 outcome variables of interest: i) a dummy variable for whether the household i got a new loan or not at time t ($1(NL_{i,t} > 0)$),[12] ii)

[12] This variable only considers the sample of households that had no consumer debt at time $t-1$. The reason is

$\frac{NL_{i,t}}{12\times P_{i,t}}$, the ratio of the new consumer loan amount to the annual permanent income for households who undertake loans (i.e, those with $NL_{i,t} > 0$), iii) $Df(\geq 1m)_{i,t}$, a dummy variable for whether the household is in arrears or not for one month or longer (considering that the household has a positive loan amount), and iv) $Df(\geq 3m)_{i,t}$, a dummy variable for whether the household is in arrears or not for 3 months or longer. The models estimated can be represented as:

1) $Y_{i,t} = G(\beta \left[Law_{c,t} \times f^c_{i,t}, f^c_{i,t}, \ln(P_{i,t}), x_{i,t}\right] + \theta_t + \eta_i + \varepsilon_{i,t}),$

where $Y_{i,t}$ is an endogenous variable of interest, $G(.)$ is a known parametric function, $Law_{c,t} \equiv 1(date^{end}_c > t > date^{beg}_c)$ is a dummy for the period in which law c is effective[13], and $f^c_{i,t}$ is a financial inclusion variable determining the groups affected by law c, with $c \in \{2010, 2011, 2012\}$). The models include controls for individual borrower characteristics ($x_{i,t}$) and time period fixed-effects (θ_t), plus an unobserved household random-effect (η_i) and an iid error-term ($\varepsilon_{i,t}$).

The time period law dummies ($Law_{c,t}$) are interacted with the financial inclusion variables ($f^c_{i,t}$) that determine the targeted groups by each legislation. In the case of the 2010 law ($f^{c=2010}_{i,t}$), I consider a continuous variable, which is the household's income weighted unemployment risk ($u_{i,t}$). This variable is chosen because the EFH-CMF dataset only registers the unemployment status of each household member at the time of the survey, although we can observe the probability that workers of similar characteristics are unemployed at each time period. As a robustness check, we also estimate regressions that use the EFH-CMF household's self-reported average unemployment rate at the time of the survey, $U^{EFH,hh}_i$.[14] In the case of the 2011 and 2012 laws ($f^{c=2011}_{i,t}$, $f^{c=2012}_{i,t}$), I consider dummy variables that are equal to the Beneficiaries of the laws of 2011 and 2012 used

that the EFH-CMF dataset only measures the households' indebtedness at each time t, but it is not a panel dataset of loans. Therefore if a household has a positive amount of debt at two or more consecutive time periods, say t and $t+1$, then it is not possible to tell whether the debt in these consecutive periods was the result of a single decision at time t or if these are two entirely different loan decisions that were made independently. For simplicity, I assume that a period of consecutive debt observations corresponds to a single loan choice of the household, and that the different loan amounts observed during consecutive periods correspond to downpayments or renegotiations of the initial loan.

[13] The 2010 and 2011 laws are still valid, therefore there is no end date. The 2012 law's information deletion ceased to have effect on January of 2017, since the credit bureau would have erased events older than 5 years anyway.

[14] This variable is slightly different from the Beneficiary of the 2010 law used in the previous section. The Beneficiary of the 2010 law was a dummy variable that considered all households that reported at least one unemployed member, that is, all households with $U^{EFH,hh}_i > 0$. The variable $U^{EFH,hh}_i$ is continuous, since it considers that households with one, two, three or more unemployed members are differently impacted by the legislation.

in the previous section. For the 2011 law, households are classified as targeted beneficiaries of the legislation if they reported that they use checks frequently or if they requested three or more consumer loan applications in the previous year. For the 2012 law, households are classified as possible beneficiaries if these reported bank loans in arrears below 2.5 million pesos at the end of 2011 or if they reported a total amount of loan arrears (including bank and non-banking debts) for a survey interview date before 2012. Tables 1, 2 and 3 provide a deep description of the beneficiaries of the 2010, 2011 and 2012 laws relative to the other borrowers.

For the discrete outcome variables $(1(NL_{i,t} > 0), Df(\geq 1m)_{i,t}, Df(\geq 3m)_{i,t})$, the functional form of $G(.)$ is taken to be the logit model. In the case of the continuous outcome variable $(\frac{NL_{i,t}}{12\times P_{i,t}})$, then $G(.)$ is taken to be the OLS model. Both the logit and OLS models can be estimated with random-effects (which are normally distributed and account for unobservable factors that affect household decisions across time periods). Estimating all models with fixed-effects does not change the results in a qualitative way, but the logit model with fixed-effects only provides consistent estimates of β and therefore cannot be used to obtain elasticities and welfare effects (Wooldridge 2010). Also, the fixed-effects of each borrower are presumably unobservable by lenders, therefore the random-effects represent a more accurate approximation of what agents observe.

The vector for additional demographic and credit history controls $(x_{i,t})$ includes: a constant, the log of the permanent monthly income of the household i at time t $(\ln(P_{i,t}))$, the number of household members reported in the EFH survey, 5-year dummies for the age of the household head at time t, the college education reported by the household head in the EFH survey (the education level is assumed to be constant over time, unlike the age), plus dummies for whether the household i at time t had an arrears event in the last year for an horizon of 1 month or more (Dummy arrears (1m) last year$_{i,t}$), a dummy for whether household had any delinquency of 1 month or more in the last 3 years (Non Ever Green last 3 years$_{i,t}$), and a dummy for whether the household has any unpaid loans in the past 5 years (Dummy unpaid loans in 5 years$_{i,t}$)[15]. Note that the EFH-CMF dataset reports all the banking credit history of each borrower between 2003 until 2018 and that this dataset was not "censored" by the 2012 information deletion law[16]. This allows me to create

[15] Note that the variable "Dummy unpaid loans in 5 years$_{i,t}$" excludes loans that fell into arrears and were repaid since then, since a Chilean law from 2002 (Law 19812, effective on June 13, 2002) excludes the history of repaid debts from the credit reports, except for Ever Green indicator and the credit scores in the last 12 months.

[16] The 2012 law only affected the credit reports available to the public and lenders, therefore it does not affect the

the delinquency history variables both as an "uncensored" version (which represents the variables known by borrowers and what lenders would see if the 2012 law had never been made) and as a "censored" version which is what the lenders could observe after the 2012 law was implemented. The creation of these "uncensored" and "censored" control variables will allow me to show the counterfactual of what would have happened if the 2012 law had not been made in the next section. For the case of the delinquency outcomes, I consider an additional variable, which is household i's monthly Banking Consumer Debt Service to Permanent Income Ratio. This last variable is not considered for the initial consumer loan decision and its amount ($1(NL_{i,t} > 0)$, $\frac{NL_{i,t}}{12 \times P_{i,t}}$), since those are taken only for the sample periods preceded by zero debt.

3.3 Calibrating the counterfactual regimes based on the empirical models

For simplicity, the counterfactual welfare exercises apply just one law and all the 3 laws simultaneously, although one could also consider combinations of 2 laws. Let the law regimes be given by $e \in \{\text{No laws, 2010 law, 2011 law, 2012 law, All laws}\}$, while $z_{i,t}^{e}$ denotes the information that lenders can observe under regime e for each borrower i at time t. The costs of making a loan equal the loan capital (standardized as one), a fixed administrative cost (FC, calibrated as 0.075[17]) plus the the cost of funds for lenders (R_t, calibrated as the banking sector's one-year deposit rate). For each debt type DT (with DT being either credit cards/lines or installment loans), the gains of making a loan are the capital plus the risk-adjusted interest rate $(1 + RIR_{i,t}^{DT})$ weighted by the probability of repayment $(1 - Df_{i,t}^{DT}(z_{i,t}^{e}))$ and in case of delinquency (with probability $Df_{i,t}^{DT}(z_{i,t}^{e})$) a fraction of the amount owed (calibrated by a Loss-Given-Default parameter, $LGD = 0.50$, as in other consumer loan studies for Chile and the US, see Madeira, 2019a). Assuming competitive zero profits, then gives us the risk-adjusted interest rate $RIR_{i,t}^{DT}(e)$:

$$2)\ (1 + FC + R_t) = (1 + RIR_{i,t}^{DT}(e)) \left[(1 - Df_{i,t}^{DT}(z_{i,t}^{e})) + (1 - LGD) \times Df_{i,t}^{DT}(z_{i,t}^{e}) \right]$$

$$\Rightarrow RIR_{i,t}^{DT}(e) = \frac{FC + R_t + LGD \times Df_{i,t}^{DT}(z_{i,t}^{e})}{1 - LGD \times Df_{i,t}^{DT}(z_{i,t}^{e})}.$$

data availability of the regulators, either the CMF or the Central Bank of Chile.

[17] This fixed cost includes the costs of loan monitoring, compulsory insurance fees, having the contract approved by a loan officer and checking its bureau's credit report (which costs 15,000 Chilean pesos), see Madeira 2019a.

Let the set of full information be $z_{i,t}^{full-\inf} \equiv \left\{Law_{c,t} \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, H_{i,t}^{censored}, \theta_t\right\}$, with the vectors $H_{i,t}^{uncensored}$ and $H_{i,t}^{censored}$ representing the delinquency information of the borrowers in its entirety (as if the 2012 law had not been implemented) and in a censored form (after the 2012 law). Let the counterfactual vector of law regime e apply just one law at each time, that is: $CL_{e,t} \equiv \{Law_{e,t} = 1, Law_{c,t} = 0 \forall c \neq e\}$. In the case of "No laws" the dummies of each law regime are set to zero ($CL_{NoLaws,t} \equiv \{Law_{c,t} = 0 \forall c\}$), therefore we have $z_{i,t}^{NoLaws} \equiv \left\{0 \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$. For the 2010 and 2011 laws the information of its beneficiaries is not observed, therefore the information set is: $z_{i,t}^{2010} \equiv \left\{CL_{2010,t}, f_{i,t}^{2011}, f_{i,t}^{2012}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$ and $z_{i,t}^{2011} \equiv \left\{CL_{2011,t}, f_{i,t}^{2010}, f_{i,t}^{2012}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$. The 2012 and All Laws regimes only observe the delinquency history $H_{i,t}^{censored}$, therefore we have: $z_{i,t}^{2012} \equiv \left\{CL_{2012,t}, f_{i,t}^{2010}, f_{i,t}^{2011}, x_{i,t}, H_{i,t}^{censored}, \theta_t\right\}$ and $z_{i,t}^{AllLaws} \equiv \left\{CL_{AllLaws,t}, x_{i,t}, H_{i,t}^{censored}, \theta_t\right\}$, with $CL_{AllLaws,t} \equiv \{Law_{c,t} = 1 \forall c\}$.

The empirical models give us an estimated delinquency risk conditional on the observable information $z_{i,t}^{e}$ at an horizon above 1 and 3 months: $Df(\geq 1m, z_{i,t}^{e}), Df(\geq 3m, z_{i,t}^{e})$. The one month horizon is as an early warning for loan problems, but many borrowers are able to recover towards a clean status. For this reason, the delinquency rate at 3 months is taken to be the most relevant risk measure, both in Chile and other countries (Madeira 2019a). For calibrating the $RIR_{i,t}^{DT}(e)$ I apply a weighted average of the 1 and 3 month risks: $Df_{i,t}^{DT}(z_{i,t}^{e}) = w_1^{DT} Df(\geq 1m, z_{i,t}^{e}) + (1 - w_1^{DT}) Df(\geq 3m, z_{i,t}^{e})$. Credit cards and lines of credit are a revolving type of loan, therefore these are more subject to short-term risk and therefore I calibrate $w_1^{CreditCards\&Lines} = 0.50$. Banking consumer installment loans have longer maturities (with an average maturity of 24 months in Chilean banks, therefore I calibrate the 1 month risk weight as $w_1^{InstallmentLoans} = 0.33$.

Let $q_{i,t}^{e}$ be the loan demand conditional on $CL_{e,t}$ and the full-information set known by borrowers $z_{i,t}^{full-\inf}$. Loan demand can be expressed in terms of the borrower's expected number of loans ($q_{i,t}^{NrLoans,e} \equiv \Pr(NL_{i,t} > 0 \mid CL_{e,t}, z_{i,t}^{full-\inf})$) or as total debt amount ($q_{i,t}^{TotalDebt,e} \equiv 12P_{i,t} \times E\left[\frac{NL_{i,t}}{12 \times P_{i,t}} \mid CL_{e,t}, z_{i,t}^{full-\inf}\right] \Pr(NL_{i,t} > 0 \mid CL_{e,t}, z_{i,t}^{full-\inf})$). Assuming zero lender profits plus an approximately linear demand function around the old and the new equilibria, the deadweight welfare loss of each law regime e for the market DT is given by:

$$3)\ DWL_{i,t}^{DT}(e) = (1 - A_{i,t}^{e,DT})(q_{i,t}^{\min(e,NoLaws)} + \tfrac{1}{2}\left|\Delta q_{i,t}^{e,NoLaws}\right|)\Delta RIR_{i,t}^{DT,e,NoLaws}$$
$$+A_{i,t}^{e,DT}(q_{i,t}^{\min(e,NoLaws)}\Delta RIR_{i,t}^{DT,e,NoLaws} - \tfrac{1}{2}(R_t^{\max} - RIR_{i,t}^{DT,\max(e,NoLaws)})\Delta q_{i,t}^{e,NoLaws}),$$

with $\Delta q_{i,t}^{e,NoLaws} = (q_{i,t}^{e} - q_{i,t}^{NoLaws})$, $\Delta RIR_{i,t}^{DT,e,NoLaws} = (RIR_{i,t}^{DT}(e) - RIR_{i,t}^{DT}(NoLaws))$, $RIR_{i,t}^{DT,\max(e,NoLaws)} = \max(RIR_{i,t}^{DT}(e), RIR_{i,t}^{DT}(NoLaws))$, $q_{i,t}^{\min(e,NoLaws)} = \min(q_{i,t}^{NoLaws}, q_{i,t}^{e})$, $A_{i,t}^{e,DT} = 1((RIR_{i,t}^{DT}(e) - RIR_{i,t}^{DT}(NoLaws))(q_{i,t}^{e} - q_{i,t}^{NoLaws}) > 0)$. The deadweight loss in a market with asymmetric information is expressed as the sum of two cases. In the first case ($A_{i,t}^{e,DT} = 0$), demand and interest rates change in opposite directions, which is the standard case in most markets: demand falls when the interest rate (the price of the loan increases). The deadweight loss in this case corresponds to a square given by the extra price that consumers are paying for a given quantity ($q_{i,t}^{\min(e,NoLaws)} \Delta RIR_{i,t}^{DT,e,NoLaws}$) plus a triangle due to the change in quantities ($\frac{1}{2}\left|\Delta q_{i,t}^{e,NoLaws}\right| \Delta RIR_{i,t}^{DT,e,NoLaws}$). In the second case ($A_{i,t}^{e,DT} = 1$), quantities and interest rates move in the same direction due to asymmetric information (i.e., the increase in risky borrowers leads lenders to increase loan prices). The deadweight loss in this case is again given by a square ($q_{i,t}^{\min(e,NoLaws)} \Delta RIR_{i,t}^{DT,e,NoLaws}$) due to the extra price paid minus a triangle ($-\frac{1}{2}(R_t^{\max} - RIR_{i,t}^{DT,\max(e,NoLaws)})\Delta q_{i,t}^{e,NoLaws}$), which is the value of the extra quantity consumed. $R_t^{\max}$ is the maximum price or interest rate that a borrower is willing to pay to obtain the first loan. In Chile there is a maximum interest rate for consumer loans fixed by law each month and therefore $R_t^{\max}$ is known and easy to calibrate (Cuesta and Sepúlveda 2019, Madeira 2019b).

4 Results

Table 4 shows the results for the Banking Consumer Installment Loans market of the full information models for credit access, consumer debt to annual permanent income, and delinquency over 1 and 3 months ($1(NL_{i,t} > 0), \frac{NL_{i,t}}{12 \times P_{i,t}}, Df(\geq 1m)_{i,t}, Df(\geq 3m)_{i,t}$). The evidence shows that the 2010 "Credit information of the unemployed" law (i.e., the coefficients estimated for the variable Law 2010 $\times$ $u_{i,t}$) had a positive impact on the credit access ($NL_{i,t} > 0$) and loan size of the unemployed ($\frac{NL_{i,t}}{12 \times P_{i,t}}$), while at the same time having an insignificant impact on the delinquency rates. The impact of the 2011 "Risk predictors' fairness" law on its beneficiaries (i.e., Law 2011 $\times$ $Beneficiary2011_i$) was somewhat mixed, since it reduced the number of credit loans ($NL_{i,t} > 0$), although it increased slightly the loan amounts ($\frac{NL_{i,t}}{12 \times P_{i,t}}$) and decreased the delinquency rates. Finally, the 2012 "Delinquency deletion" law had a negative impact on the credit access ($NL_{i,t} > 0$) and the delinquency rates of its beneficiaries (i.e., Law 2012 $\times$ $Beneficiary2011_i$).

Table 4: New loan decision, debt to permanent income ratio and delinquency for Consumer Installment Loans

Full information models ($z_{i,t}^{full-\inf} \equiv \left\{Law_{c,t} \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$)

Variables	$NL_{i,t} > 0$ (Logit)	$\frac{NL_{i,t}}{12 \times P_{i,t}}$ (OLS)	$Df(\geq 1m)_{i,t}$ (Logit)	$Df(\geq 3m)_{i,t}$ (Logit)
Law 2010$_t$ $\times$ $u_{i,t}$	6.846***	0.596***	-0.199	0.440
	(0.751)	(0.127)	(0.500)	(1.312)
Law 2011$_t$ $\times$	-0.633***	0.0143*	-0.273***	-0.147*
$Beneficiary2011_i$	(0.0574)	(0.00795)	(0.0309)	(0.0889)
Law 2012$_t$ $\times$	-0.629***	-0.0110	-0.252***	-0.505***
$Beneficiary2012_i$	(0.0500)	(0.00833)	(0.0320)	(0.0972)
$u_{i,t}$	-4.402***	-0.266***	1.669*	2.788*
	(0.571)	(0.0742)	(0.918)	(1.470)
$Beneficiary2011_i$	0.650***	0.0282***	-0.388***	-0.562***
	(0.0402)	(0.00388)	(0.0624)	(0.0981)
$Beneficiary2012_i$	0.469***	0.0280***	1.566***	0.482***
	(0.0291)	(0.00361)	(0.0520)	(0.0935)
$\ln(P_{i,t})$	0.176***	-0.0883***	-0.00538	-0.0162
	(0.0192)	(0.00281)	(0.0371)	(0.0541)
Household size$_i$	-0.0338***	-0.00243**	0.106***	0.0421*
	(0.00850)	(0.00114)	(0.0164)	(0.0232)
College educ.$_i$	0.425***	0.0506***	-0.433***	-0.553***
	(0.0334)	(0.00422)	(0.0627)	(0.0902)
Dummy arrears	0.927***	-0.00447	1.635***	5.917***
(1m): last year$_{i,t}$	(0.0457)	(0.00688)	(0.0207)	(0.356)
Non Ever Green	-0.386***	0.00775	0.689***	0.956**
last 3 years$_{i,t}$	(0.0374)	(0.00596)	(0.0219)	(0.390)
Dummy unpaid	-0.154***	0.00534	0.369***	1.044***
loans in 5 years$_{i,t}$	(0.0505)	(0.00830)	(0.0193)	(0.0353)
Bank Debt			1.308***	1.949***
Service Ratio$_{i,t}$			(0.0530)	(0.121)
Random-effects$_i$	Yes	Yes	Yes	Yes
Pseudo R2	0.078	0.265	0.287	0.152
Obs: $N \times T$ / N	962,587 / 7,790	21,212 / 7,787	516,687 / 7,619	516,687 / 7,619

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

Before the legislations were passed (i.e., the controls $u_{i,t}$, $Beneficiary2011_i$, $Beneficiary2012_i$) one finds as expected that unemployment risk is associated with lower credit access, smaller loans and higher delinquency rates. The 2011 beneficiaries were associated with higher credit access and larger loans and presented lower delinquency rates, which confirms the previous findings that the check-users are richer households (Table 1) and better loan payers (Table 3) relative to other borrowers. Interestingly, before the 2012 legislation, its beneficiaries had higher credit access, larger loans but showed significantly higher default rates, which is an indicator that these were borrowers that benefitted from the trust of lenders but then incurred into repayment problems.

The evidence is similar for credit cards and lines of credit. The 2010 "Credit information of the unemployed" law had a positive impact for the unemployed on the probability of getting a loan and the loan amounts, while having no impact on the delinquency rates. The 2011 "Risk predictors' fairness" law decreased credit access. The 2012 "Delinquency deletion" law had a negative impact on both credit access and loan size, although it also reduced the delinquency rates (perhaps because lenders were more selective about borrowers). Before the legislation, unemployment risk was associated with lower credit access, while the beneficiaries of the 2011 law (check-users) were associated with higher credit access, larger loans and lower delinquency rates, and the beneficiaries of the 2012 law were associated with both higher credit access, larger loans and higher delinquency.

The other controls exhibit the expected signs. College education, higher income, smaller household size and lower unemployment risk are all associated with better loan access and lower delinquency, either for consumer installment loans (Table 4) or credit cards/lines (Table 5). The dummies for arrears in the last year, Non Ever Green (i.e., with a delinquency event in the last 3 years) and unpaid loans in the last 5 years are powerful and statistically significant predictors of delinquency risk at both horizons, whether in installment loans or credit cards/lines (Tables 4 and 5). The Non Ever Green and unpaid loans in the last 5 years dummy are negatively associated with credit access either in installment loans or credit cards/lines (Tables 4 and 5). That is not the case for the dummy of arrears of 1 month in the last year, perhaps because such arrears can happen due to inattention or small problems and therefore are not heavily penalized by banks.

Results are robust to re-estimating the models in Tables 4 and 5 by replacing the unemployment risk $u_{i,t}$ variable with other measures for the beneficiaries of the 2010 law, such as the household's self-reported fraction of members in unemployment, $U_i^{EFH,hh}$, or a dummy for whether there is any

Table 5: New loan decision, debt to permanent income ratio and delinquency for Credit Cards and Lines
Full information models ($z_{i,t}^{full-\inf} \equiv \left\{Law_{c,t} \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$)

Variables	$NL_{i,t} > 0$ (Logit)	$\frac{NL_{i,t}}{12 \times P_{i,t}}$ (OLS)	$Df(\geq 1m)_{i,t}$ (Logit)	$Df(\geq 3m)_{i,t}$ (Logit)
Law $2010_t \times u_{i,t}$	3.247***	0.447***	0.524	2.444
	(0.909)	(0.121)	(0.620)	(1.803)
Law $2011_t \times$	-0.189***	-4.56e-05	0.00809	0.0925
$Beneficiary2011_i$	(0.0611)	(0.00645)	(0.0340)	(0.0947)
Law $2012_t \times$	-0.953***	-0.0116*	-0.157***	-0.384***
$Beneficiary2012_i$	(0.0488)	(0.00661)	(0.0319)	(0.0821)
$u_{i,t}$	-4.232***	-0.345***	1.432*	-1.198
	(0.783)	(0.0994)	(0.866)	(1.731)
$Beneficiary2011_i$	0.790***	0.0339***	-0.420***	-0.307***
	(0.0521)	(0.00479)	(0.0553)	(0.0917)
$Beneficiary2012_i$	0.314***	0.0509***	0.969***	0.189**
	(0.0362)	(0.00416)	(0.0453)	(0.0745)
$\ln(P_{i,t})$	0.410***	-0.0682***	-0.211***	-0.196***
	(0.0253)	(0.00281)	(0.0310)	(0.0408)
Household size$_i$	-0.106***	0.000350	0.101***	0.0147
	(0.0114)	(0.00114)	(0.0141)	(0.0185)
College educ.$_i$	0.831***	0.0263***	-0.444***	-0.169**
	(0.0442)	(0.00383)	(0.0522)	(0.0673)
Dummy arrears	0.617***	0.0120*	1.643***	4.352***
(1m): last year$_{i,t}$	(0.0485)	(0.00665)	(0.0254)	(0.170)
Non Ever Green	-0.759***	0.0157***	0.558***	0.691***
last 3 years$_{i,t}$	(0.0389)	(0.00526)	(0.0268)	(0.184)
Dummy unpaid	-0.662***	-0.00824	0.302***	0.478***
loans in 5 years$_{i,t}$	(0.0656)	(0.00884)	(0.0218)	(0.0398)
Bank Debt			0.151***	-0.485***
Service Ratio$_{i,t}$			(0.0501)	(0.0914)
Random-effects$_i$	Yes	Yes	Yes	Yes
Pseudo R2 or R2	0.121	0.171	0.196	0.090
Obs: $N \times T$ / N	1,062,803 / 8,649	30,769 / 8,649	568,265 / 8,473	568,265 / 8,473

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

unemployed member in the household, $Beneficiary2010_i = 1(U_i^{EFH,hh} > 0)$. The results are also robust to including random-effects or not. These exercises are available as an online appendix.

The models in Tables 4 and 5 include all the information that would be observed by either borrowers and lenders before the laws were implemented. Therefore to calibrate the impact of the decreased information that is known to lenders, I must re-estimate the same models without the variables affected by each law, which include the measures of the law's beneficiaries ($Law_{c,t} \times f_{i,t}^c$, $f_{i,t}^c$ for $c = e$) and in case of the 2012 law a "censored" version of the past delinquency indicators, $H_{i,t}^{censored}$. Table 6 shows the results of these "partial information" delinquency risk models for both Consumer Installment Loans and Credit Cards/Lines of Credit. The results are similar to the "full information" models reported in Tables 4 and 5, with past delinquency indicators being significant predictors of current delinquency. Curiously, the "censored" variables have similar coefficient values as the "uncensored" ones, showing that lenders still trusted the reliability of the credit bureau, except that such historical delinquency is now not observable for some borrowers. Also, just like in Tables 4 and 5, the beneficiaries of the 2012 law and unemployment risk are positively associated with delinquency for both consumer installment loans and for credit cards/lines, while the beneficiaries of the 2011 law (users of checks) are negatively associated with delinquency risk.

5 Policy implications

Figure 2 shows the random-effects models' implied counterfactual changes in the risk-adjusted interest rates ($RIR_{i,t}^{DT}(e) - RIR_{i,t}^{DT}(NoLaws)$), probability of getting a loan ($\frac{q_{i,t}^{NrLoans,e}}{q_{i,t}^{NrLoans,NoLaws}}$) and total debt ($\frac{q_{i,t}^{TotalDebt,e}}{q_{i,t}^{TotalDebt,NoLaws}}$) after the new law regimes. Another figure in the online appendix of the working paper shows very similar results for the models estimated with no random-effects. The figure discards the 10% lower and upper tails to allow a better focus on the center of the distributions. The counterfactual results are qualitatively similar for both credit cards/lines and installment loans. Both for credit cards/lines and installment loans, the 2010 law implied a reduction in interest rates of 0.25% to 0.5% for a large number of borrowers, while a smaller fraction of borrowers experienced an increase of 0 to 0.25% in interest rates. For a significant number of

Table 6: Delinquency risk model when some variables are deleted

Partial information models ($z^e_{i,t}$, with e =2010 law, 2011 law, 2012 law, All laws)

	Banking Consumer Installment Loans							
	$Df(\geq 1m)_{i,t}$ (Logit)				$Df(\geq 3m)_{i,t}$ (Logit)			
Variables	2010 Law	2011 Law	2012 Law	All Laws	2010 Law	2011 Law	2012 Law	All Laws
$u_{i,t}$		1.705*	1.502			2.692*	2.913**	
		(0.922)	(0.943)			(1.474)	(1.428)	
$Beneficiary2011_i$	-0.393***		-0.396***		-0.561***		-0.536***	
	(0.0624)		(0.0641)		(0.0980)		(0.0953)	
$Beneficiary2012_i$	1.565***	1.563***			0.478***	0.466***		
	(0.0520)	(0.0522)			(0.0935)	(0.0937)		
	Uncensored variables		Censored variables		Uncensored variables		Censored variables	
Dummy arrears	1.635***	1.636***	1.512***	1.512***	5.917***	5.918***	5.336***	5.342***
(1m): last year$_{i,t}$	(0.0207)	(0.0207)	(0.0223)	(0.0223)	(0.356)	(0.356)	(0.270)	(0.271)
Non Ever Green	0.689***	0.687***	0.825***	0.823***	0.957**	0.973**	0.898***	0.905***
last 3 years$_{i,t}$	(0.0219)	(0.0219)	(0.0233)	(0.0233)	(0.390)	(0.390)	(0.278)	(0.279)
Dummy unpaid	0.369***	0.372***	0.410***	0.413***	1.043***	1.044***	1.134***	1.134***
loans in 5 years$_{i,t}$	(0.0193)	(0.0193)	(0.0195)	(0.0195)	(0.0353)	(0.0353)	(0.0349)	(0.0349)
Obs: $N \times T$ / N				516,687	/ 7,619			
	Credit Cards and Lines of Credit							
	$Df(\geq 1m)_{i,t}$ (Logit)				$Df(\geq 3m)_{i,t}$ (Logit)			
Variables	2010 Law	2011 Law	2012 Law	All Laws	2010 Law	2011 Law	2012 Law	All Laws
$u_{i,t}$		1.683*	1.529*			-0.989	-1.126	
		(0.867)	(0.869)			(1.722)	(1.728)	
$Beneficiary2011_i$	-0.423***		-0.423***		-0.296***		-0.297***	
	(0.0552)		(0.0555)		(0.0913)		(0.0916)	
$Beneficiary2012_i$	0.966***	0.971***			0.182**	0.191**		
	(0.0453)	(0.0455)			(0.0743)	(0.0746)		
	Uncensored variables		Censored variables		Uncensored variables		Censored variables	
Dummy arrears	1.643***	1.643***	1.524***	1.524***	4.352***	4.354***	4.002***	4.004***
(1m): last year$_{i,t}$	(0.0254)	(0.0254)	(0.0275)	(0.0275)	(0.170)	(0.170)	(0.161)	(0.162)
Non Ever Green	0.558***	0.558***	0.679***	0.678***	0.692***	0.697***	1.016***	1.021***
last 3 years$_{i,t}$	(0.0268)	(0.0268)	(0.0284)	(0.0284)	(0.184)	(0.184)	(0.172)	(0.172)
Dummy unpaid	0.302***	0.301***	0.357***	0.356***	0.478***	0.475***	0.536***	0.534***
loans in 5 years$_{i,t}$	(0.0218)	(0.0218)	(0.0220)	(0.0220)	(0.0399)	(0.0398)	(0.0395)	(0.0395)
Obs: $N \times T$ / N				568,265	/ 8,473			

Other controls (all regressions): Time fixed-effects, $\ln(P_{i,t})$, Household size$_i$, College education$_i$, Bank Debt Service Ratio$_{i,t}$, 5-year age dummies of the household head, plus $Law_{c,t} \times f^c_{i,t}$ for $c \neq e$. Random-effects$_i$ included. Robust Standard-errors in (). ***,**,* denote 1%, 5% and 10% statistical significance.

borrowers the odds of obtaining a loan after the 2010 law increased between 0 to 15% for credit cards and between 0% to 30% for installment loans. Finally, a significant number of borrowers benefitted from an increase in total credit amounts between 0 to 30% for credit cards/lines and between 0 to 40% for installment loans. The 2011 law also implied a reduction in interest rates (between 0 to 0.75% for credit cards/lines and between 0 to 1.25% for installment loans) for a significant fraction of the borrowers, but for some borrowers it implied a moderate (around 10%) and a large decrease (around 40%) in loan probability and debt amounts for credit cards/lines and installment loans, respectively. The 2012 law had even more heterogeneous effects than the 2011 law. After the 2012 law a small number of borrowers benefitted from a decrease in interest rates of 1% to 2% for credit cards and 2.5% to 3.5% for installment loans, which is a sizeable reduction in interest rates[18]. However, a much larger number of borrowers saw an increase in interest rates of 0.5% to 1% for credit cards and 0.5% to 1.5% for installment loans. Also, the 2012 law decreased the total loan amount by 50% for a significant fraction of the borrowers, either for credit cards/lines or installment loans. The counterfactual of "All Laws" in terms of its effects is somewhat closer to the 2012 law for both credit cards/lines and installment loans, which makes sense since, as shown in Table 1, this law affected a larger fraction of the Chilean population. A small fraction of the population benefitted from a large decrease in interest rates, while a much larger number of borrowers experienced an increase in interest rates. In terms of loan access and total debt, the result shows a significant fraction of borrowers experiencing a decrease in loan access and total debt (as expected from both the 2011 and 2012 laws), while another fraction of the borrowers experienced an increase in loan access and total debt (as expected from the 2012 law's beneficiaries).

To show the heterogeneity of the welfare impact, I compute the sum of the total deadweight loss and income of the household over the period in which all of the laws were effective: $DWL_i^e = \sum_t DWL_{i,t}^e$ and $P_i = \sum_t P_{i,t}$. Table 7 shows the aggregate impact of the laws in terms of the total borrower income and the percentage of borrowers affected across All borrowers plus Borrowers with and without college. The results show that the 2010 law implied a welfare gain around 0.08%, while the 2011 law implied almost zero loss and the 2012 law implied a welfare loss of 0.175% of borrowers' income. In terms of the fraction of the population with losses, the 2010 law appears to

[18] The estimates for the impact of the 2012 law are consistent with the simulations of Liberman et al. (2018), who also find that the 2012 law harmed around two thirds of the borrowers.

Figure 2: Counterfactual change in the distribution (pdf, percentiles 10 to 90) of the risk-adjusted interest rates (percentage points), the odds ratio of obtaining a banking consumer loan and the total debt after the laws: models with random-effects

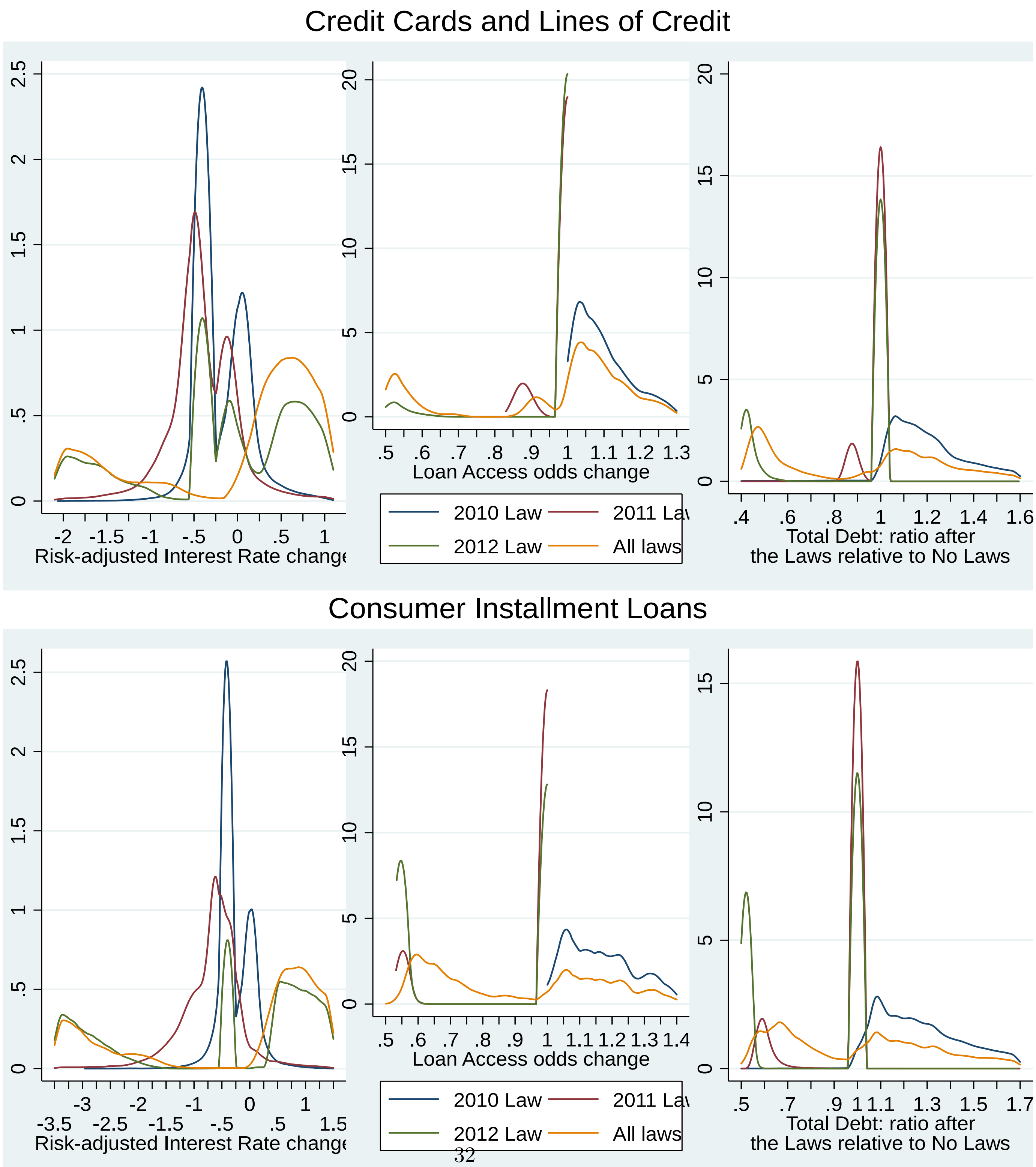

Table 7: Deadweight welfare loss (DWL) implied by the new laws
Period in which all laws are effective (Feb, 2012 until Dec, 2016)
Models with random-effects

	$\frac{\sum_i DWL_i^e}{\sum_i P_i}$ (DWL in % of aggregate borrowers' income)				Fraction of borrowers with positive DWL_i^e (in %)			
Market / Law	2010	2011	2012	All Laws	2010	2011	2012	All Laws
	All borrowers (with banking consumer debt between 2003-2018)							
Total Debt	-0.082	0.001	0.175	0.127	0.2	18.7	92.9	44.8
Credit cards/lines	-0.104	-0.021	0.268	0.198	0.1	19.9	86.9	48.1
Installment Loans	-0.064	0.023	0.113	0.095	0.2	18.1	93.8	42.0
	Borrowers without college education							
Total Debt	-0.082	-0.020	0.194	0.133	0.0	12.0	94.5	43.3
Credit cards/lines	-0.101	-0.028	0.285	0.210	0.0	13.8	89.2	49.3
Installment Loans	-0.063	-0.007	0.123	0.078	0.0	11.3	94.7	38.4
	Borrowers with college education or higher							
Total Debt	-0.083	0.013	0.148	0.119	0.4	40.3	87.5	48.8
Credit cards/lines	-0.109	-0.009	0.237	0.178	0.1	39.9	79.1	44.2
Installment Loans	-0.065	0.062	0.099	0.117	0.3	38.7	91.0	52.9

Note that the denominator of Total Debt differs from Credit cards/lines and Installment loans due to the number of borrowers with joint debts.

be a clear success, since the number of losers was only 0.1%. The 2011 law impacted negatively less than 20% of the borrowers, although the fraction of "losers" was 40% among the college educated. The 2012 law implied losses for over 90% of the borrower population. Overall, the All Laws regime harmed almost 45% of the borrowers and implied a welfare loss of 0.127% of the income. Also, welfare losses were bigger for Credit card users and for non-college educated people.

I now analyze the heterogeneity of losses and gains across winners, losers and the distribution across percentiles of different households. Table 8 shows that the 2010 law had only a small impact on the "losers" (that is, the borrowers suffering welfare losses) and a significant impact on the "winners" (the borrowers with welfare gains). The results also show that the 2011 law had a significant negative impact on some borrowers, especially on the users of Installment Loans (with the percentile 75 of the losers suffering a loss of 0.357% of its income). However, the "losers" are less than 20% of the borrowers (Table 7) and therefore these amount to a small impact in aggregate terms. The 2012 law and the "All Laws" regime implied significant welfare losses (corresponding to 0.187% and 0.225% of the losers' income), especially on Credit Card users at the percentile 75 (which lost 0.7% and 0.8% of their income, respectively). At the same time the 2012 law had very small benefits even for the less than 10% of the borrowers (Table 7) that benefitted from this law.

Table 8: Heterogeneity of the deadweight loss (DWL) implied by the new laws
Period in which all laws are effective (Feb, 2012 until Dec, 2016)
Models with random-effects

	Borrowers with losses: $DWL_i^e > 0$				Borrowers with gains: $DWL_i^e \leq 0$			
Market / Law	2010	2011	2012	All Laws	2010	2011	2012	All Laws
	$\frac{\sum_i DWL_i^e}{\sum_i P_i}$ Fraction of DWL in aggregate borrowers' income (in %)							
Total Debt	0.001	0.088	0.187	0.225	-0.082	-0.056	-0.008	-0.065
Credit cards/lines	0.001	0.057	0.306	0.392	-0.104	-0.061	-0.008	-0.087
Installment Loans	0.002	0.169	0.123	0.165	-0.064	-0.052	-0.011	-0.049
	$\frac{DWL_i^e}{P_i}$ (in %): Percentile 25							
Total Debt	0.000	0.064	0.036	0.067	-0.142	-0.086	-0.013	-0.108
Credit cards/lines	0.000	0.024	0.028	0.113	-0.166	-0.089	-0.012	-0.150
Installment Loans	0.000	0.152	0.046	0.040	-0.113	-0.085	-0.045	-0.078
	$\frac{DWL_i^e}{P_i}$ (in %): Median							
Total Debt	0.001	0.139	0.100	0.223	-0.094	-0.052	-0.006	-0.061
Credit cards/lines	0.001	0.084	0.108	0.435	-0.114	-0.055	-0.006	-0.083
Installment Loans	0.002	0.235	0.101	0.117	-0.067	-0.044	-0.012	-0.044
	$\frac{DWL_i^e}{P_i}$ (in %): Percentile 75							
Total Debt	0.002	0.235	0.408	0.465	-0.068	-0.033	-0.003	-0.037
Credit cards/lines	0.002	0.169	0.720	0.826	-0.037	-0.027	-0.003	-0.016
Installment Loans	0.003	0.357	0.232	0.246	-0.055	-0.031	-0.003	-0.026

Note that the Borrowers with losses or gains for one law are not the same as those for other laws.

It is interesting to note that the 2010, 2011 and the All Laws regimes had a welfare gain of 0.082%, 0.056% and 0.065% of income, respectively, for its "winners" (borrowers with negative deadweight loss). There was some heterogeneity in gains across "winners", although to a smaller degree than among "losers", with the range between the percentiles 25 and 75 going from 0.068%, 0.033%, 0.037%, to 0.142%, 0.086% and 0.108% of income for the 2010, 2011 and All Laws regimes.

6 Conclusions

This work shows the impact on the banking consumer loan market of three laws that reduced the information in the Chilean credit bureau: the law on "Credit information of the unemployed" (2010), the law on "Risk predictors' fairness" (2011) and the law on "Delinquency deletion" (2012). Using a unique matched dataset of the banking system supervisor's administrative records and the Chilean Household Finance Survey (EFH), I find that the 2010 law had a positive effect on loan access, total credit and welfare, while the 2012 law implied a large reduction in welfare and the 2011 law had a very small impact. Furthermore, the 2010 and 2012 laws were also extremely different in the heterogeneity of their impact. While the 2010 law harmed almost no borrower, the 2011 law was of little benefit for less than 10% of the borrowers, while harming over 90% of the borrowers, accumulating to a clear welfare loss in the aggregate. Overall, since the 2012 law was the legislation with the greatest impact, the combined effect of the three laws together was negative for welfare, although some borrowers benefitted from higher credit access.

These results confirm the theoretical predictions that information deletion laws can have an ambiguous impact on welfare, depending on how they affect the moral hazard of the agents and their risk-sharing. The 2010 law is a good example of how a well-designed legislation can reduce information in the credit bureau to a positive effect for borrowers, since it targets only the short-term unemployed (a non-strategic delinquency reason) and it only delays the release of negative information for a brief period therefore it should limit moral hazard. The 2012 law on the other hand made a permanent delinquency deletion and unrelated to its motives. The last three decades saw an expansion in the coverage and information available in credit bureaus and registries across the world, with many previous studies highlighting the positive effects of this information expansion (World Bank 2020). Therefore the differences found in the welfare impact of these laws should have an impact on how regulators think about changes in their credit bureaus and registries.

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7 Appendix

This appendix provides robustness checks to the empirical estimates in the main article. The appendix figure is a robustness check of Figure 2 in the article. The appendix figure uses the models of Tables 4, 5 and 6 estimated without random-effects, while the Figure 2 in the main article uses models with random-effects to build the counterfactual measures. The estimates of the models without random effects are available in Tables A.1, A.2 and A.3.

Tables A.4 and A.5 are other robustness checks of Tables 4 and 5, respectively, by replacing the unemployment risk $u_{i,t}$ variable with another measures for the beneficiaries of the 2010 law, which is a dummy variable for whether there is any unemployed member in the household, $Beneficiary2010_i = 1(U_i^{EFH,hh} > 0)$. Note that the coefficients of the variable $Beneficiary2010_i$ and its interaction term with the 2010 law are smaller in size than the values reported in Tables 4 and 5, but that is due to the scale of the variables (one is a dummy variable with values 0 or 1, while another is unemployment risk taking values around 0.025 to 0.25). In the same way, the variable $U_i^{EFH,hh}$ can take values exactly equal to zero (if no member in the household is unemployed), 0.5 (say, if one member of a couple is unemployed) or 1 (if all members in the household are unemployed), although it can take other values for large families. Tables A.6 and A.7 are also robustness checks of Tables 4 and 5, but replace unemployment risk with the household's self-reported fraction of members in unemployment, $U_i^{EFH,hh}$.

All the results in these exercises are similar to the main article.

Table A.1: New loan decision, debt to permanent income ratio and delinquency for Consumer Installment Loans
Full information models ($z_{i,t}^{full-\inf} \equiv \left\{ Law_{c,t} \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t \right\}$)
Models estimated without random-effects

Variables	$NL_{i,t} > 0$ (Logit)	$\frac{NL_{i,t}}{12 \times P_{i,t}}$ (OLS)	$Df(\geq 1m)_{i,t}$ (Logit)	$Df(\geq 3m)_{i,t}$ (Logit)
Law $2010_t \times u_{i,t}$	5.747***	0.527***	-0.126	-2.479***
	(0.479)	(0.104)	(0.368)	(0.823)
Law 2011_t ×	-0.550***	0.0172***	-0.208***	-0.101*
$Beneficiary2011_i$	(0.0327)	(0.00665)	(0.0238)	(0.0593)
Law 2012_t ×	-0.569***	-0.00171	-0.489***	-0.326***
$Beneficiary2012_i$	(0.0343)	(0.00748)	(0.0242)	(0.0685)
$u_{i,t}$	-3.376***	-0.170***	0.260	2.738***
	(0.357)	(0.0576)	(0.268)	(0.617)
$Beneficiary2011_i$	0.574***	0.0184***	-0.151***	-0.274***
	(0.0205)	(0.00275)	(0.0152)	(0.0394)
$Beneficiary2012_i$	0.364***	0.0213***	0.854***	0.0449
	(0.0182)	(0.00285)	(0.0145)	(0.0462)
$\ln(P_{i,t})$	0.155***	-0.0823***	-0.0599***	-0.0668***
	(0.0108)	(0.00200)	(0.00776)	(0.0189)
Household size$_i$	-0.0261***	-0.00215**	0.0408***	0.00564
	(0.00492)	(0.000867)	(0.00361)	(0.00839)
College educ.$_i$	0.370***	0.0429***	-0.203***	-0.238***
	(0.0177)	(0.00307)	(0.0131)	(0.0321)
Dummy arrears	0.924***	-0.00325	1.639***	5.730***
(1m): last year$_{i,t}$	(0.0368)	(0.00714)	(0.0182)	(0.354)
Non Ever Green	-0.267***	0.00820	0.672***	0.760*
last 3 years$_{i,t}$	(0.0295)	(0.00574)	(0.0189)	(0.405)
Dummy unpaid	-0.0726*	0.0117	0.554***	1.506***
loans in 5 years$_{i,t}$	(0.0388)	(0.00791)	(0.0148)	(0.0274)
Bank Debt			0.180***	0.595***
Service Ratio$_{i,t}$			(0.0210)	(0.0496)
Random-effects$_i$	No	No	No	No
Pseudo R2	0.088	0.269	0.236	0.408
Obs: $N \times T$ / N	962,587 / 7,790	21,212 / 7,787	516,687 / 7,619	516,687 / 7,619

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

Table A.2: New loan decision, debt to permanent income ratio and delinquency for Credit Cards and Lines
Full information models ($z_{i,t}^{full-\inf} \equiv \left\{Law_{c,t} \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$)
Models estimated without random-effects

Variables	$NL_{i,t} > 0$ (Logit)	$\frac{NL_{i,t}}{12 \times P_{i,t}}$ (OLS)	$Df(\geq 1m)_{i,t}$ (Logit)	$Df(\geq 3m)_{i,t}$ (Logit)
Law $2010_t \times u_{i,t}$	4.866***	0.321***	-0.571	1.390
	(0.432)	(0.0833)	(0.462)	(1.286)
Law 2011_t $\times$	-0.286***	0.00706	-0.00812	0.126*
$Beneficiary2011_i$	(0.0256)	(0.00441)	(0.0270)	(0.0715)
Law 2012_t $\times$	-0.778***	-0.0102*	-0.294***	-0.381***
$Beneficiary2012_i$	(0.0287)	(0.00572)	(0.0263)	(0.0681)
$u_{i,t}$	-4.020***	-0.230***	1.507***	-1.019
	(0.372)	(0.0694)	(0.402)	(1.188)
$Beneficiary2011_i$	0.681***	0.0230***	-0.220***	-0.237***
	(0.0193)	(0.00306)	(0.0210)	(0.0614)
$Beneficiary2012_i$	0.164***	0.0457***	0.506***	-0.0192
	(0.0166)	(0.00300)	(0.0174)	(0.0490)
$\ln(P_{i,t})$	0.262***	-0.0642***	-0.134***	-0.156***
	(0.00890)	(0.00167)	(0.00907)	(0.0223)
Household size$_i$	-0.0819***	0.000893	0.0570***	0.00336
	(0.00423)	(0.000736)	(0.00433)	(0.0104)
College educ.$_i$	0.553***	0.00981***	-0.205***	-0.0330
	(0.0144)	(0.00244)	(0.0151)	(0.0356)
Dummy arrears	0.628***	-6.98e-05	1.770***	4.237***
(1m): last year$_{i,t}$	(0.0366)	(0.00769)	(0.0229)	(0.168)
Non Ever Green	-0.555***	0.0311***	0.571***	0.366**
last 3 years$_{i,t}$	(0.0258)	(0.00532)	(0.0234)	(0.182)
Dummy unpaid	-0.505***	0.0105	0.347***	0.919***
loans in 5 years$_{i,t}$	(0.0430)	(0.00923)	(0.0175)	(0.0308)
Bank Debt			0.00537	-0.387***
Service Ratio$_{i,t}$			(0.0238)	(0.0583)
Random-effects$_i$	No	No	No	No
Pseudo R2 or R2	0.103	0.122	0.209	0.350
Obs: $N \times T$ / N	1,062,803 / 8,649	30,769 / 8,649	568,265 / 8,473	568,265 / 8,473

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

Table A.3: Delinquency risk model when some variables are deleted
Partial information models ($z^{e}_{i,t}$, with e =2010 law, 2011 law, 2012 law, All laws)
Models with no random-effects

	Banking Consumer Installment Loans							
	$Df(\geq 1m)_{i,t}$ (Logit)				$Df(\geq 3m)_{i,t}$ (Logit)			
Variables	2010 Law	2011 Law	2012 Law	All Laws	2010 Law	2011 Law	2012 Law	All Laws
$u_{i,t}$		0.118	0.641**			2.487***	2.707***	
		(0.267)	(0.261)			(0.613)	(0.618)	
$Beneficiary2011_i$	-0.152***		-0.171***		-0.278***		-0.275***	
	(0.0151)		(0.0149)		(0.0392)		(0.0394)	
$Beneficiary2012_i$	0.854***	0.853***			0.0460	0.0342		
	(0.0145)	(0.0145)			(0.0462)	(0.0462)		
	Uncensored variables		Censored variables		Uncensored variables		Censored variables	
Dummy arrears	1.639***	1.638***	1.571***	1.570***	5.731***	5.733***	5.218***	5.226***
(1m): last year$_{i,t}$	(0.0182)	(0.0182)	(0.0193)	(0.0193)	(0.354)	(0.354)	(0.176)	(0.177)
Non Ever Green	0.672***	0.678***	0.973***	0.978***	0.757*	0.771*	1.156***	1.154***
last 3 years$_{i,t}$	(0.0189)	(0.0189)	(0.0192)	(0.0191)	(0.405)	(0.405)	(0.191)	(0.191)
Dummy unpaid	0.554***	0.558***	0.532***	0.537***	1.506***	1.510***	1.544***	1.549***
loans in 5 years$_{i,t}$	(0.0148)	(0.0147)	(0.0147)	(0.0147)	(0.0274)	(0.0274)	(0.0274)	(0.0274)
Obs: $N \times T$ / N				516,687 / 7,619				
	Credit Cards and Lines of Credit							
	$Df(\geq 1m)_{i,t}$ (Logit)				$Df(\geq 3m)_{i,t}$ (Logit)			
Variables	2010 Law	2011 Law	2012 Law	All Laws	2010 Law	2011 Law	2012 Law	All Laws
$u_{i,t}$		1.541***	1.788***			-0.831	-1.308	
		(0.399)	(0.389)			(1.172)	(1.189)	
$Beneficiary2011_i$	-0.223***		-0.236***		-0.230***		-0.228***	
	(0.0209)		(0.0205)		(0.0611)		(0.0614)	
$Beneficiary2012_i$	0.505***	0.507***			-0.0221	-0.0199		
	(0.0174)	(0.0174)			(0.0489)	(0.0489)		
	Uncensored variables		Censored variables		Uncensored variables		Censored variables	
Dummy arrears	1.770***	1.769***	1.683***	1.684***	4.237***	4.239***	3.762***	3.763***
(1m): last year$_{i,t}$	(0.0230)	(0.0229)	(0.0240)	(0.0240)	(0.168)	(0.168)	(0.113)	(0.113)
Non Ever Green	0.570***	0.575***	0.762***	0.765***	0.367**	0.369**	0.811***	0.814***
last 3 years$_{i,t}$	(0.0234)	(0.0234)	(0.0237)	(0.0237)	(0.182)	(0.182)	(0.120)	(0.120)
Dummy unpaid	0.348***	0.345***	0.339***	0.338***	0.920***	0.918***	0.940***	0.940***
loans in 5 years$_{i,t}$	(0.0175)	(0.0175)	(0.0175)	(0.0175)	(0.0308)	(0.0308)	(0.0308)	(0.0308)
Obs: $N \times T$ / N				568,265 / 8,473				

Other controls (all regressions): Time fixed-effects, $\ln(P_{i,t})$, Household size$_i$, College education$_i$, Bank Debt Service Ratio$_{i,t}$, 5-year age dummies of the household head, plus $Law_{c,t} \times f^{c}_{i,t}$ for $c \neq e$. Random-effects$_i$ not included. Robust Standard-errors in (). ***,**,* denote 1%, 5% and 10% statistical significance.

Figure 3: Counterfactual change in the distribution (pdf, percentiles 10 to 90) of the risk-adjusted interest rates (percentage points), loan probability and total debt after the laws: models without random-effects and with unemployment risk interacted with the 2010 law

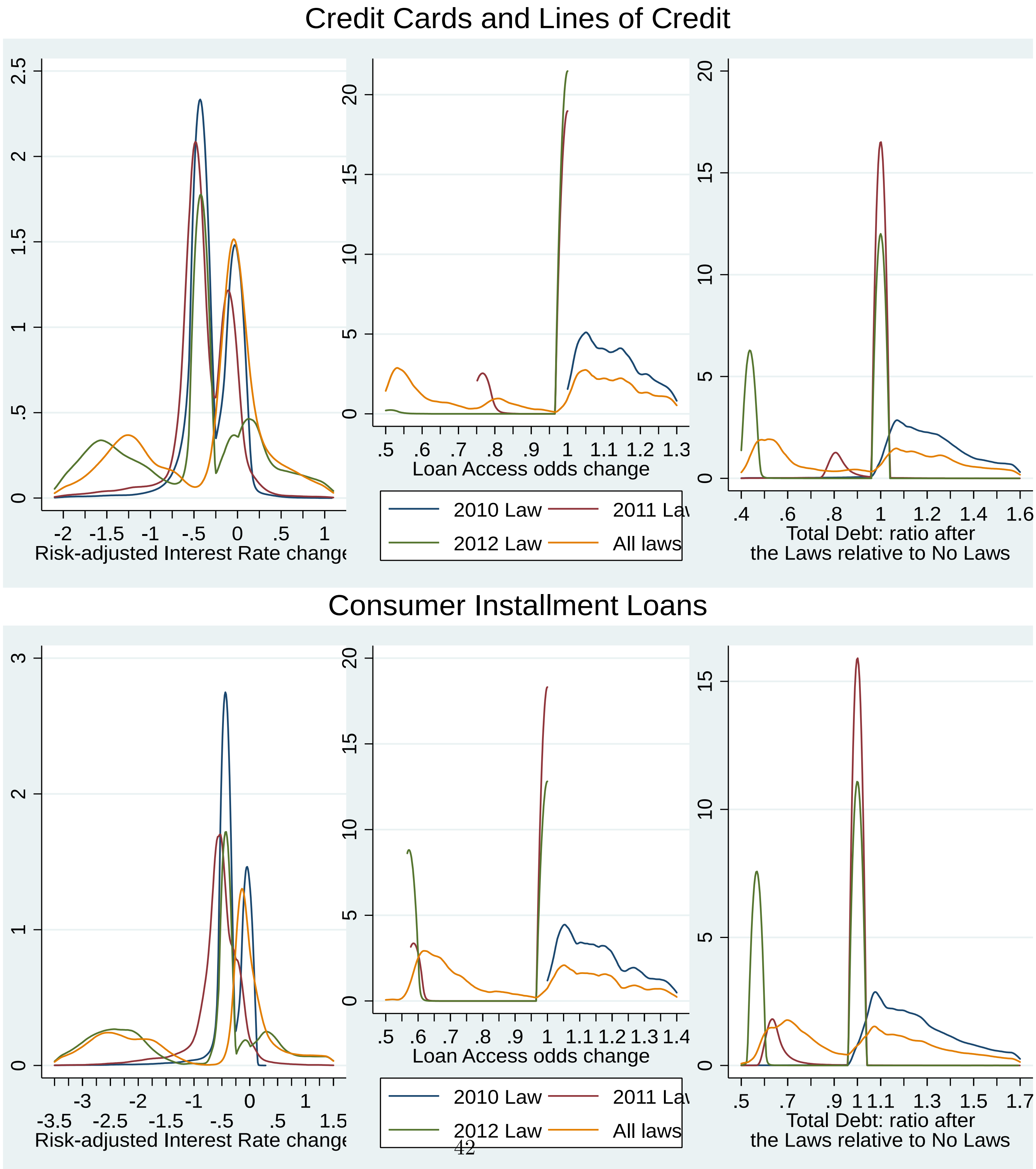

Table A.4: New loan decision, debt to permanent income ratio and delinquency for Consumer Installment Loans: using a dummy for a self-reported unemployment status of a household member in the EFH survey, $Beneficiary2010_i = 1(U_i^{EFH,hh} > 0)$, interacted with the 2010 law.
Full information models ($z_{i,t}^{full-\inf} \equiv \left\{ Law_{c,t} \times f_{i,t}^c, f_{i,t}^c, x_{i,t}, H_{i,t}^{uncensored}, \theta_t \right\}$)

Variables	$NL_{i,t} > 0$ (Logit)		$\frac{NL_{i,t}}{12 \times P_{i,t}}$ (OLS)		$Df(\geq 1m)_{i,t}$ (Logit)		$Df(\geq 3m)_{i,t}$ (Logit)	
Law 2010_t ×	0.147***	0.198**	-0.0445***	-0.0428***	-0.0857**	-0.208***	-0.0565	0.506***
$Beneficiary2010_i$	(0.0480)	(0.0770)	(0.00901)	(0.0105)	(0.0334)	(0.0451)	(0.0801)	(0.124)
Law 2011_t ×	-0.621***	-0.711***	0.00867	0.00540	-0.211***	-0.282***	-0.0854	-0.138
$Beneficiary2011_i$	(0.0321)	(0.0566)	(0.00648)	(0.00783)	(0.0234)	(0.0307)	(0.0588)	(0.0886)
Law 2012_t ×	-0.555***	-0.615***	-0.000699	-0.00973	-0.489***	-0.252***	-0.326***	-0.503***
$Beneficiary2012_i$	(0.0342)	(0.0501)	(0.00748)	(0.00834)	(0.0242)	(0.0320)	(0.0684)	(0.0973)
$Beneficiary2010_i$	-0.174***	-0.187***	0.00797*	0.00969	0.130***	0.328***	0.0136	-0.268**
	(0.0314)	(0.0529)	(0.00470)	(0.00619)	(0.0226)	(0.0807)	(0.0555)	(0.130)
$Beneficiary2011_i$	0.599***	0.678***	0.0206***	0.0306***	-0.147***	-0.381***	-0.277***	-0.570***
	(0.0204)	(0.0399)	(0.00275)	(0.00390)	(0.0152)	(0.0624)	(0.0393)	(0.0985)
$Beneficiary2012_i$	0.355***	0.458***	0.0204***	0.0268***	0.854***	1.564***	0.0461	0.475***
	(0.0181)	(0.0291)	(0.00285)	(0.00360)	(0.0145)	(0.0519)	(0.0462)	(0.0938)
$\ln(P_{i,t})$	0.166***	0.192***	-0.0828***	-0.0882***	-0.0622***	-0.0233	-0.0822***	-0.0524
	(0.0104)	(0.0186)	(0.00192)	(0.00269)	(0.00752)	(0.0358)	(0.0184)	(0.0524)
Household size_i	-0.0273***	-0.0379***	-0.00176**	-0.00229**	0.0389***	0.104***	0.00960	0.0510**
	(0.00487)	(0.00844)	(0.000864)	(0.00113)	(0.00362)	(0.0164)	(0.00838)	(0.0233)
College educ._i	0.371***	0.427***	0.0428***	0.0506***	-0.202***	-0.433***	-0.248***	-0.568***
	(0.0177)	(0.0333)	(0.00306)	(0.00422)	(0.0130)	(0.0626)	(0.0319)	(0.0906)
Dummy arrears	0.923***	0.925***	-0.00347	-0.00475	1.639***	1.633***	5.731***	5.926***
(1m): last $\text{year}_{i,t}$	(0.0367)	(0.0456)	(0.00715)	(0.00689)	(0.0182)	(0.0207)	(0.354)	(0.356)
Non Ever Green	-0.263***	-0.382***	0.00784	0.00756	0.673***	0.691***	0.758*	0.962**
last 3 $\text{years}_{i,t}$	(0.0295)	(0.0374)	(0.00574)	(0.00597)	(0.0189)	(0.0219)	(0.405)	(0.390)
Dummy unpaid	-0.0661*	-0.144***	0.0125	0.00628	0.555***	0.370***	1.506***	1.038***
loans in 5 $\text{years}_{i,t}$	(0.0388)	(0.0504)	(0.00792)	(0.00836)	(0.0148)	(0.0193)	(0.0275)	(0.0353)
Bank Debt					0.173***	1.302***	0.583***	1.950***
Service $\text{Ratio}_{i,t}$					(0.0210)	(0.0529)	(0.0495)	(0.121)
Random-effects_i	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R2	0.088	0.078	0.269	0.265	0.237	0.287	0.408	0.152
Obs: $N \times T$ / N	962,587 / 7,790		21,212 / 7,787		516,687 / 7,619		516,687 / 7,619	

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

Table A.5: New loan decision, debt to permanent income ratio and delinquency for Credit Cards and Lines: using a dummy for a self-reported unemployment status of a household member in the EFH survey, $Beneficiary2010_i = 1(U_i^{EFH,hh} > 0)$, interacted with the 2010 law.
Full information models ($z_{i,t}^{full-\inf} \equiv \left\{ Law_{c,t} \times f_{i,t}^c, f_{i,t}^c, x_{i,t}, H_{i,t}^{uncensored}, \theta_t \right\}$)

Variables	$NL_{i,t} > 0$ (Logit)		$\frac{NL_{i,t}}{12 \times P_{i,t}}$ (OLS)		$Df(\geq 1m)_{i,t}$ (Logit)		$Df(\geq 3m)_{i,t}$ (Logit)	
Law 2010$_t$ $\times$	0.162***	0.120	-0.00262	-0.00723	0.143***	0.115**	0.152	0.217
$Beneficiary2010_i$	(0.0410)	(0.0886)	(0.00710)	(0.00949)	(0.0456)	(0.0581)	(0.123)	(0.166)
Law 2011$_t$ $\times$	-0.334***	-0.219***	0.00364	-0.00457	-0.00262	0.00377	0.119*	0.0754
$Beneficiary2011_i$	(0.0253)	(0.0603)	(0.00429)	(0.00625)	(0.0267)	(0.0335)	(0.0708)	(0.0937)
Law 2012$_t$ $\times$	-0.771***	-0.951***	-0.00960*	-0.0108	-0.295***	-0.157***	-0.380***	-0.382***
$Beneficiary2012_i$	(0.0287)	(0.0487)	(0.00573)	(0.00662)	(0.0263)	(0.0319)	(0.0681)	(0.0821)
$Beneficiary2010_i$	-0.169***	-0.207***	-0.00119	-0.000302	-0.0958**	-0.0155	-0.126	-0.114
	(0.0325)	(0.0721)	(0.00555)	(0.00764)	(0.0380)	(0.0778)	(0.110)	(0.153)
$Beneficiary2011_i$	0.708***	0.810***	0.0244***	0.0358***	-0.226***	-0.422***	-0.233***	-0.298***
	(0.0191)	(0.0518)	(0.00301)	(0.00473)	(0.0209)	(0.0552)	(0.0612)	(0.0913)
$Beneficiary2012_i$	0.158***	0.312***	0.0451***	0.0499***	0.506***	0.967***	-0.0220	0.183**
	(0.0166)	(0.0362)	(0.00300)	(0.00415)	(0.0174)	(0.0453)	(0.0489)	(0.0743)
$\ln(P_{i,t})$	0.273***	0.435***	-0.0639***	-0.0676***	-0.146***	-0.231***	-0.158***	-0.205***
	(0.00856)	(0.0246)	(0.00160)	(0.00266)	(0.00880)	(0.0299)	(0.0214)	(0.0394)
Household size$_i$	-0.0834***	-0.109***	0.000912	0.000319	0.0592***	0.103***	0.00334	0.0145
	(0.00422)	(0.0114)	(0.000729)	(0.00113)	(0.00434)	(0.0141)	(0.0104)	(0.0185)
College educ.$_i$	0.556***	0.837***	0.0102***	0.0269***	-0.209***	-0.446***	-0.0331	-0.167**
	(0.0144)	(0.0442)	(0.00243)	(0.00384)	(0.0150)	(0.0522)	(0.0356)	(0.0672)
Dummy arrears	0.629***	0.618***	-0.000354	0.0117*	1.771***	1.643***	4.237***	4.353***
(1m): last year$_{i,t}$	(0.0366)	(0.0485)	(0.00770)	(0.00665)	(0.0230)	(0.0254)	(0.168)	(0.170)
Non Ever Green	-0.551***	-0.758***	0.0313***	0.0158***	0.569***	0.558***	0.367**	0.692***
last 3 years$_{i,t}$	(0.0258)	(0.0389)	(0.00533)	(0.00527)	(0.0234)	(0.0268)	(0.182)	(0.184)
Dummy unpaid	-0.506***	-0.662***	0.0106	-0.00794	0.348***	0.301***	0.919***	0.477***
loans in 5 years$_{i,t}$	(0.0431)	(0.0657)	(0.00924)	(0.00885)	(0.0175)	(0.0218)	(0.0308)	(0.0398)
Bank Debt					0.00314	0.148***	-0.386***	-0.484***
Service Ratio$_{i,t}$					(0.0238)	(0.0501)	(0.0583)	(0.0914)
Random-effects$_i$	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R2	0.104	0.088	0.121	0.171	0.209	0.115	0.350	0.090
Obs: $N \times T$ / N	1,062,803 / 8,649		30,769 / 8,649		568,265 / 8,473		568,265 / 8,473	

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

Table A.6: New loan decision, debt to permanent income ratio and delinquency for Consumer Installment Loans: using $U_i^{EFH,hh}$, the self-reported fraction of household members in unemployment in the EFH survey, interacted with the 2010 law.

Full information models ($z_{i,t}^{full-\inf} \equiv \left\{Law_{c,t} \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$)

Variables	$NL_{i,t} > 0$ (Logit)		$\frac{NL_{i,t}}{12 \times P_{i,t}}$ (OLS)		$Df(\geq 1m)_{i,t}$ (Logit)		$Df(\geq 3m)_{i,t}$ (Logit)	
Law 2010$_t$ $\times U_i^{EFH,hh}$	2.621***	3.157***	0.0108	0.0583	-0.332*	-0.313	-1.404***	0.0442
	(0.412)	(0.596)	(0.0695)	(0.0776)	(0.193)	(0.225)	(0.410)	(0.610)
Law 2011$_t$ $\times$	-0.591***	-0.679***	0.0104	0.00762	-0.211***	-0.275***	-0.0945	-0.153*
$Beneficiary2011_i$	(0.0324)	(0.0570)	(0.00656)	(0.00791)	(0.0235)	(0.0307)	(0.0588)	(0.0885)
Law 2012$_t$ $\times$	-0.560***	-0.620***	-0.00152	-0.0107	-0.489***	-0.252***	-0.328***	-0.508***
$Beneficiary2012_i$	(0.0342)	(0.0501)	(0.00749)	(0.00835)	(0.0242)	(0.0320)	(0.0684)	(0.0973)
$U_i^{EFH,hh}$	-2.165***	-2.565***	0.0117	-0.0241	0.340***	0.283*	0.844***	-0.443
	(0.394)	(0.588)	(0.0600)	(0.0712)	(0.131)	(0.161)	(0.252)	(0.445)
$Beneficiary2011_i$	0.588***	0.666***	0.0202***	0.0301***	-0.150***	-0.392***	-0.274***	-0.562***
	(0.0205)	(0.0401)	(0.00277)	(0.00392)	(0.0152)	(0.0624)	(0.0393)	(0.0981)
$Beneficiary2012_i$	0.359***	0.462***	0.0205***	0.0271***	0.854***	1.564***	0.0442	0.478***
	(0.0182)	(0.0291)	(0.00285)	(0.00361)	(0.0145)	(0.0520)	(0.0462)	(0.0936)
$\ln(P_{i,t})$	0.154***	0.178***	-0.0827***	-0.0884***	-0.0599***	-0.0209	-0.0799***	-0.0556
	(0.0106)	(0.0189)	(0.00195)	(0.00273)	(0.00757)	(0.0359)	(0.0185)	(0.0524)
Household size$_i$	-0.0264***	-0.0359***	-0.00210**	-0.00253**	0.0407***	0.110***	0.00862	0.0517**
	(0.00491)	(0.00845)	(0.000861)	(0.00113)	(0.00360)	(0.0163)	(0.00834)	(0.0230)
College educ.$_i$	0.370***	0.426***	0.0431***	0.0510***	-0.204***	-0.437***	-0.247***	-0.568***
	(0.0177)	(0.0333)	(0.00307)	(0.00423)	(0.0130)	(0.0626)	(0.0320)	(0.0902)
Dummy arrears	0.924***	0.926***	-0.00368	-0.00492	1.639***	1.635***	5.729***	5.918***
(1m): last year$_{i,t}$	(0.0367)	(0.0456)	(0.00716)	(0.00690)	(0.0182)	(0.0207)	(0.354)	(0.356)
Non Ever Green	-0.265***	-0.383***	0.00811	0.00789	0.673***	0.689***	0.759*	0.959**
last 3 years$_{i,t}$	(0.0295)	(0.0374)	(0.00575)	(0.00598)	(0.0189)	(0.0219)	(0.405)	(0.390)
Dummy unpaid	-0.0688*	-0.149***	0.0125	0.00616	0.554***	0.369***	1.507***	1.042***
loans in 5 years$_{i,t}$	(0.0388)	(0.0505)	(0.00793)	(0.00835)	(0.0148)	(0.0193)	(0.0275)	(0.0353)
Bank Debt					0.179***	1.305***	0.583***	1.942***
Service Ratio$_{i,t}$					(0.0210)	(0.0529)	(0.0495)	(0.121)
Random-effects$_i$	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R2	0.088	0.078	0.268	0.264	0.236	0.287	0.408	0.152
Obs: $N \times T$ / N	962,587 / 7,790		21,212 / 7,787		516,687 / 7,619		516,687 / 7,619	

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

Table A.7: New loan decision, debt to permanent income ratio and delinquency for Credit Cards and Lines: using , the self-reported fraction of household members in unemployment in the EFH survey, interacted with the 2010 law.

Full information models ($z_{i,t}^{full-\inf} \equiv \left\{Law_{c,t} \times f_{i,t}^{c}, f_{i,t}^{c}, x_{i,t}, H_{i,t}^{uncensored}, \theta_t\right\}$)

Variables	$NL_{i,t} > 0$ (Logit)		$\frac{NL_{i,t}}{12\times P_{i,t}}$ (OLS)		$Df(\geq 1m)_{i,t}$ (Logit)		$Df(\geq 3m)_{i,t}$ (Logit)	
Law 2010$_t$ $\times U_i^{EFH,hh}$	2.222***	1.134**	0.0527	0.0872*	0.184	0.157	0.854	1.138
	(0.443)	(0.495)	(0.0496)	(0.0507)	(0.229)	(0.288)	(0.658)	(0.741)
Law 2011$_t$ $\times$	-0.314***	-0.210***	0.00418	-0.00352	-0.00382	0.00407	0.122*	0.0792
$Beneficiary2011_i$	(0.0257)	(0.0605)	(0.00432)	(0.00628)	(0.0268)	(0.0336)	(0.0710)	(0.0938)
Law 2012$_t$ $\times$	-0.774***	-0.951***	-0.00975*	-0.0111*	-0.294***	-0.157***	-0.382***	-0.385***
$Beneficiary2012_i$	(0.0287)	(0.0488)	(0.00572)	(0.00662)	(0.0263)	(0.0319)	(0.0681)	(0.0822)
$U_i^{EFH,hh}$	-1.974***	-0.883*	-0.0682	-0.0856*	0.201	0.188	-0.0570	-0.0285
	(0.433)	(0.470)	(0.0474)	(0.0472)	(0.201)	(0.256)	(0.608)	(0.676)
$Beneficiary2011_i$	0.698***	0.809***	0.0241***	0.0354***	-0.224***	-0.423***	-0.235***	-0.299***
	(0.0193)	(0.0519)	(0.00303)	(0.00474)	(0.0209)	(0.0552)	(0.0613)	(0.0914)
$Beneficiary2012_i$	0.161***	0.313***	0.0452***	0.0502***	0.506***	0.967***	-0.0154	0.189**
	(0.0166)	(0.0362)	(0.00300)	(0.00415)	(0.0174)	(0.0453)	(0.0490)	(0.0744)
$\ln(P_{i,t})$	0.266***	0.432***	-0.0643***	-0.0680***	-0.143***	-0.228***	-0.151***	-0.196***
	(0.00870)	(0.0247)	(0.00162)	(0.00267)	(0.00884)	(0.0299)	(0.0215)	(0.0395)
Household size$_i$	-0.0832***	-0.112***	0.000947	0.000277	0.0587***	0.104***	0.00193	0.0136
	(0.00422)	(0.0113)	(0.000726)	(0.00113)	(0.00432)	(0.0140)	(0.0103)	(0.0184)
College educ.$_i$	0.556***	0.838***	0.0102***	0.0269***	-0.207***	-0.447***	-0.0289	-0.166**
	(0.0144)	(0.0442)	(0.00244)	(0.00384)	(0.0150)	(0.0522)	(0.0356)	(0.0672)
Dummy arrears	0.628***	0.618***	-0.000355	0.0117*	1.771***	1.643***	4.240***	4.354***
(1m): last year$_{i,t}$	(0.0366)	(0.0485)	(0.00770)	(0.00665)	(0.0230)	(0.0254)	(0.168)	(0.170)
Non Ever Green	-0.553***	-0.758***	0.0313***	0.0158***	0.569***	0.558***	0.364**	0.692***
last 3 years$_{i,t}$	(0.0258)	(0.0389)	(0.00533)	(0.00527)	(0.0234)	(0.0268)	(0.182)	(0.184)
Dummy unpaid	-0.506***	-0.663***	0.0105	-0.00819	0.348***	0.301***	0.917***	0.476***
loans in 5 years$_{i,t}$	(0.0431)	(0.0657)	(0.00924)	(0.00884)	(0.0175)	(0.0218)	(0.0308)	(0.0399)
Bank Debt					0.00221	0.150***	-0.385***	-0.485***
Service Ratio$_{i,t}$					(0.0238)	(0.0501)	(0.0583)	(0.0914)
Random-effects$_i$	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R2	0.103	0.088	0.121	0.171	0.209	0.115	0.350	0.090
Obs: $N \times T$ / N	1,062,803 / 8,649		30,769 / 8,649		568,265 / 8,473		568,265 / 8,473	

Other controls (all regressions): Time fixed-effects, 5-year dummies for age of the household head.

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistical significance.

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